Challenges in inferring radiative feedbacks from observations of Earth's energy budget

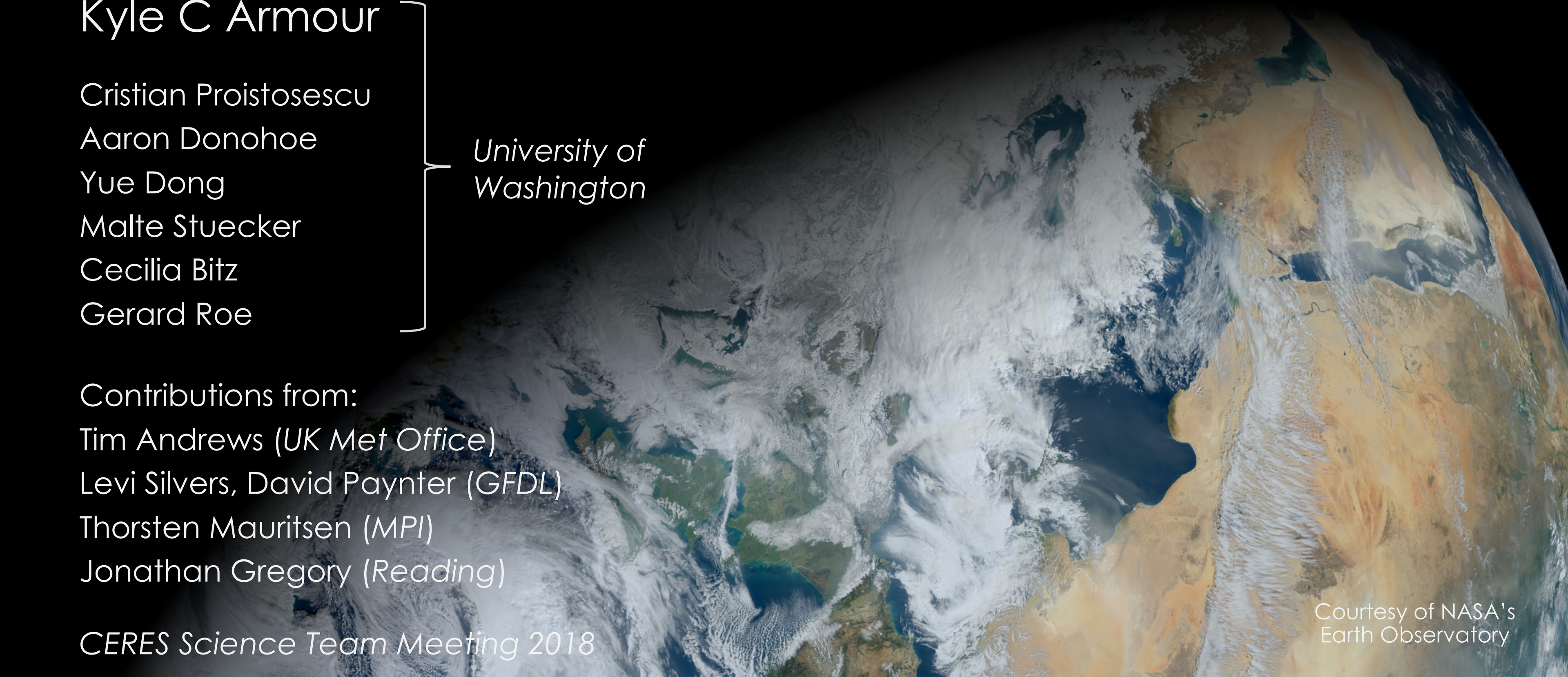
Kyle C Armour

Cristian Proistosescu
Aaron Donohoe
Yue Dong
Malte Stuecker
Cecilia Bitz
Gerard Roe

University of Washington

Contributions from:
Tim Andrews (*UK Met Office*)
Levi Silvers, David Paynter (*GFDL*)
Thorsten Mauritsen (*MPI*)
Jonathan Gregory (*Reading*)

CERES Science Team Meeting 2018



Courtesy of NASA's Earth Observatory

Standard Model of global climate response to forcing

- Linearization of global top-of-atmosphere (TOA) energy budget

$$Q = \lambda T + F$$

Q: global TOA radiation flux anomaly [Wm^{-2}]

λT: global TOA radiative response to warming [$Wm^{-2}K^{-1}$][K]

F: global TOA radiative forcing [Wm^{-2}]

Standard Model of global climate response to forcing

- Linearization of global top-of-atmosphere (TOA) energy budget

$$Q = \lambda T + F$$

Q	λT	F
global TOA radiation flux anomaly [Wm^{-2}]	global TOA radiative response to warming [$Wm^{-2}K^{-1}$][K]	global TOA radiative forcing [Wm^{-2}]

- Equilibrium warming (Q=0) in response to a doubling of atmospheric CO_2 (forcing $F_{2\times} \approx 3.7$ Wm^{-2}):

$$\mathrm{ECS} = -\frac{F_{2\times}}{\lambda}$$

Equilibrium climate sensitivity (ECS)

Estimating climate sensitivity should be easy… right?

- All we need to do is estimate the net radiative feedback λ

$$Q = \lambda T + F$$

Estimating climate sensitivity should be easy… right?

- All we need to do is estimate the net radiative feedback λ

$$Q = \lambda T + F$$

  - Method #1: Get λ from regression of $Q - F$ against T over the CERES record

Estimating climate sensitivity should be easy... right?

- All we need to do is estimate the net radiative feedback λ

$$Q = \lambda T + F$$

  - Method #1: Get λ from regression of $Q - F$ against T over the CERES record
  - Method #2: $\lambda = \dfrac{\Delta Q - \Delta F}{\Delta T}$, where Δ represents a change relative to pre-industrial

Estimating climate sensitivity should be easy… right?

- All we need to do is estimate the net radiative feedback λ

$$Q = \lambda T + F$$

  - Method #1: Get λ from regression of $Q - F$ against T over the CERES record
  - Method #2: $\lambda = \dfrac{\Delta Q - \Delta F}{\Delta T}$, where Δ represents a change relative to pre-industrial

- **Conclusions up front**: There are a variety of distinct radiative feedbacks governing Earth's radiative response to warming, and feedback estimated from either method probably doesn't provide a reliable estimate of the feedback governing long-term warming

Estimating climate sensitivity should be easy… right?

- All we need to do is estimate the net radiative feedback λ $$Q = \lambda T + F$$
    - Method #1: Get λ from regression of $Q - F$ against T over the CERES record
    - Method #2: $\lambda = \dfrac{\Delta Q - \Delta F}{\Delta T}$, where Δ represents a change relative to pre-industrial
- **Conclusions up front**: There are a variety of distinct radiative feedbacks governing Earth's radiative response to warming, and feedback estimated from either method probably doesn't provide a reliable estimate of the feedback governing long-term warming
    - Good news! CMIP5 models are generally consistent with radiative feedbacks estimated by either method when treated in a consistent way

Estimating climate sensitivity should be easy... right?

- All we need to do is estimate the net radiative feedback λ

$$Q = \lambda T + F$$

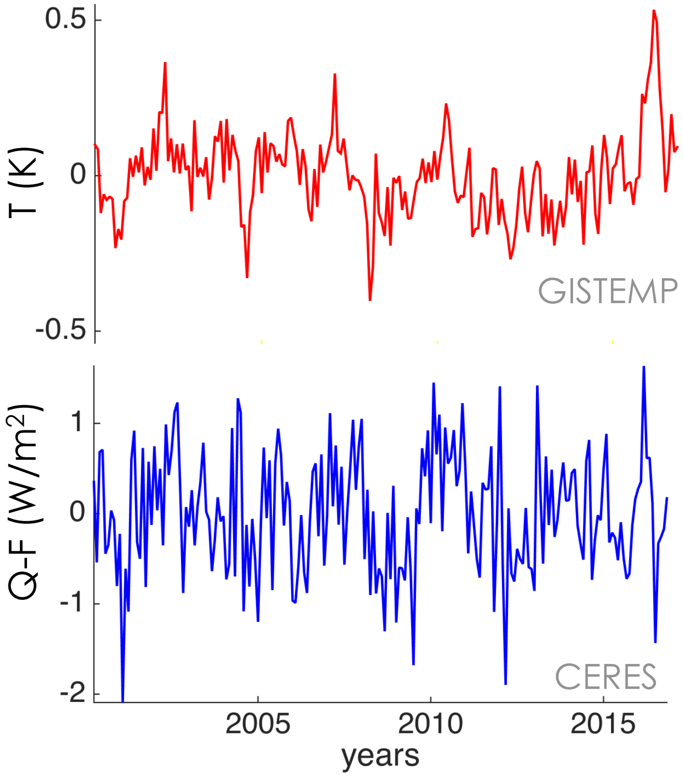
  - Method #1: Get λ from regression of $Q - F$ against T over the CERES record
  - Method #2: $\lambda = \dfrac{\Delta Q - \Delta F}{\Delta T}$, where Δ represents a change relative to pre-industrial

- **Conclusions up front**: There are a variety of distinct radiative feedbacks governing Earth's radiative response to warming, and feedback estimated from either method probably doesn't provide a reliable estimate of the feedback governing long-term warming
  - Good news! CMIP5 models are generally consistent with radiative feedbacks estimated by either method when treated in a consistent way
  - Bad news! Poses a major challenge for constraining long-term warming from short climate records; CMIP5 models suggest feedbacks will change over time as the pattern of warming evolves, resulting in high ECS and large future warming

Regression-based feedbacks

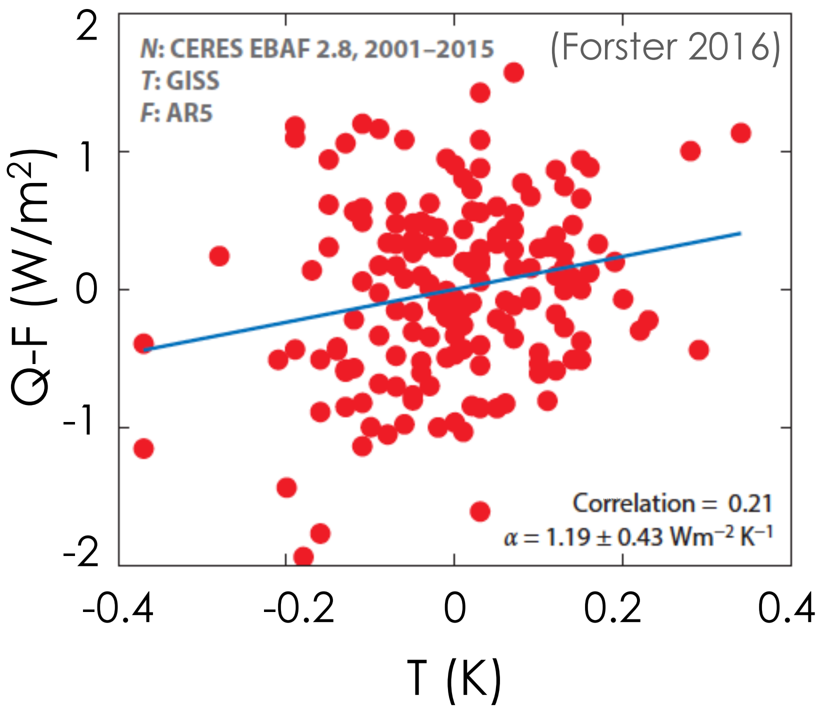
CERES-EBAF and NASA GISTEMP
March 2000 to November 2017

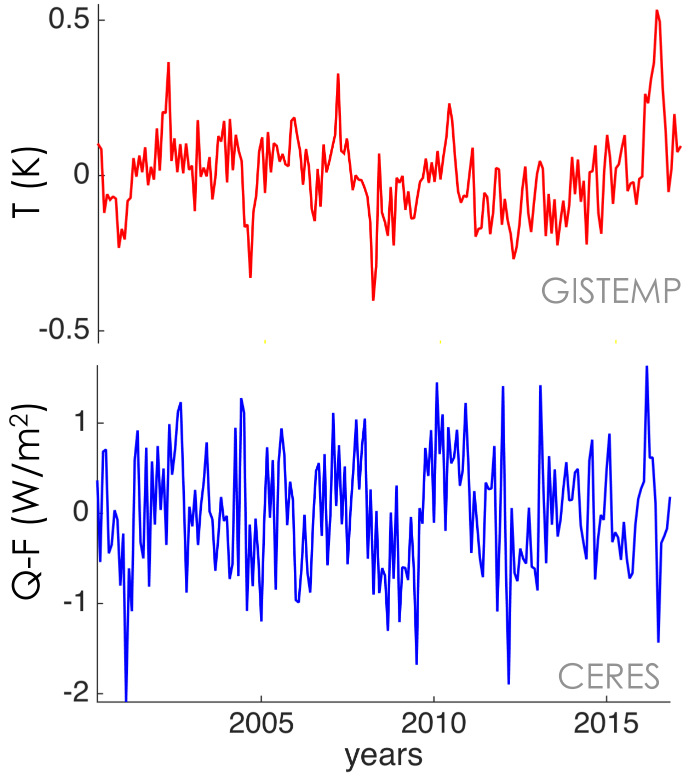
Radiative forcing (F) subtracted from global TOA radiation (Q) according to Donohoe et al (2014)



(Forster & Gregory 2006, Murphy 2009, Trenberth et al 2010, Dessler 2010, Donohoe et al 2014, Zhou et al 2015)

Regression-based feedbacks

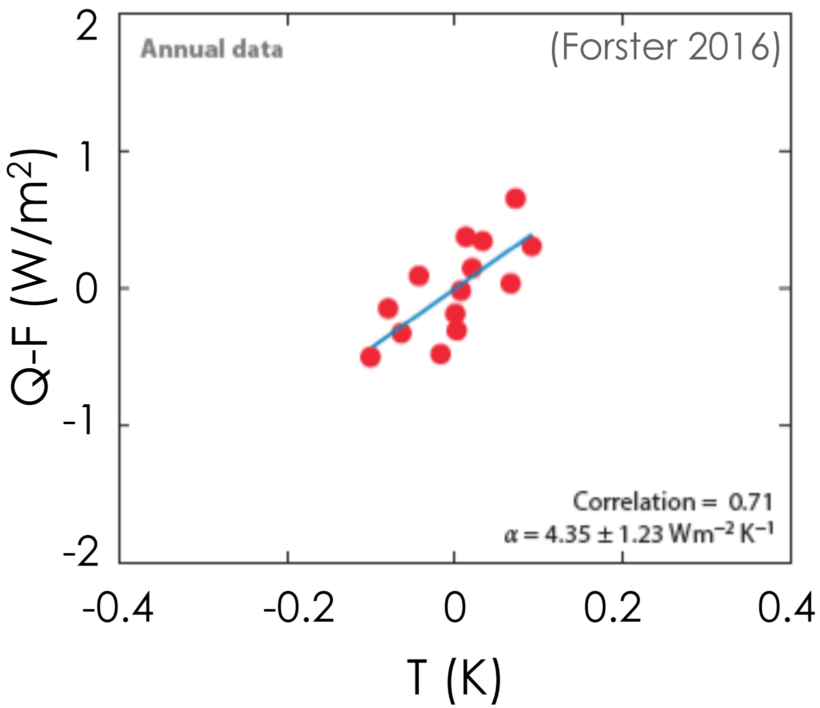




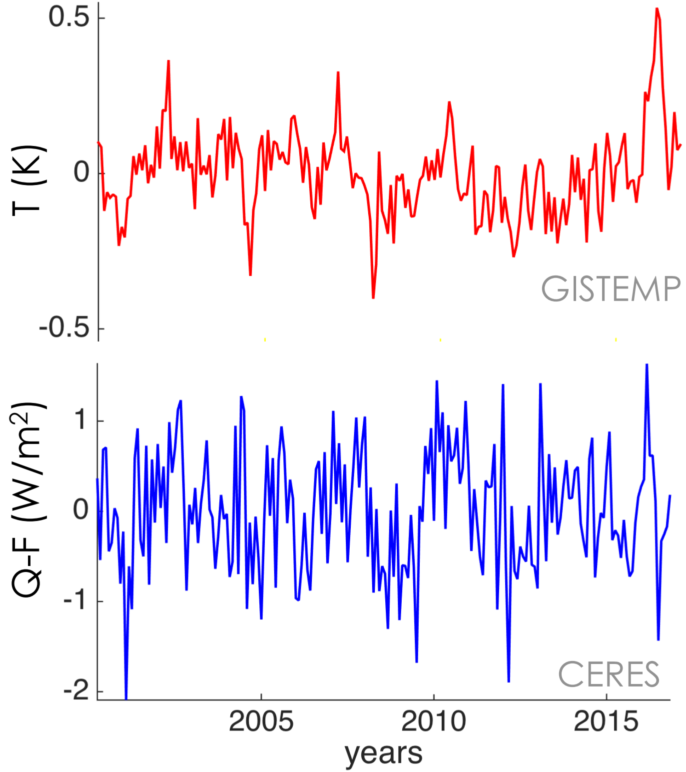
Regressing **monthly** data implies ECS = 3.1 K (2.0-7.6K, 5-95%)

(Forster & Gregory 2006, Murphy 2009, Trenberth et al 2010, Dessler 2010, Donohoe et al 2014, Zhou et al 2015)

Regression-based feedbacks

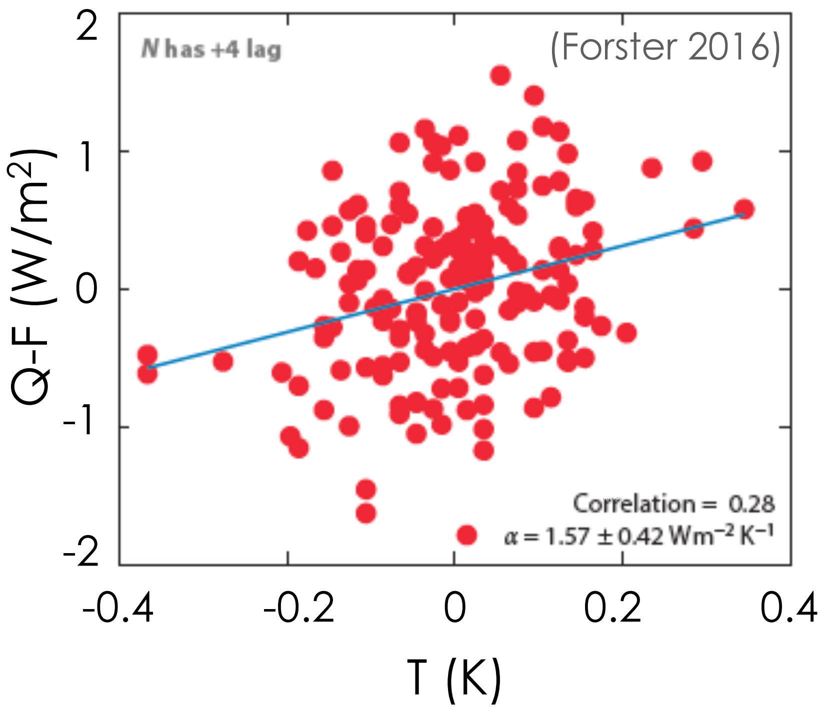


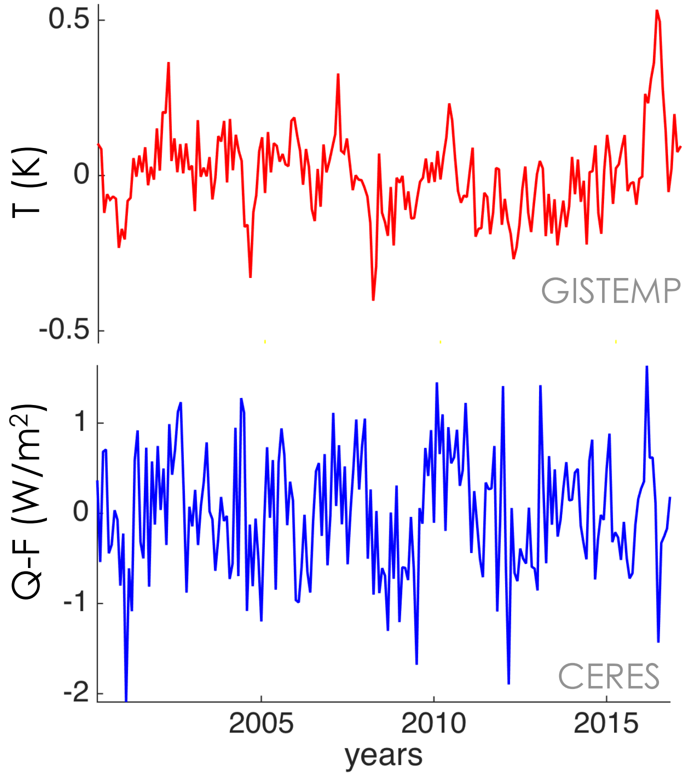
Regressing **annual** data
implies ECS = 0.9 K (0.6-1.6K, 5-95%)



(Forster & Gregory 2006, Murphy 2009, Trenberth et al 2010, Dessler 2010, Donohoe et al 2014, Zhou et al 2015)

Regression-based feedbacks

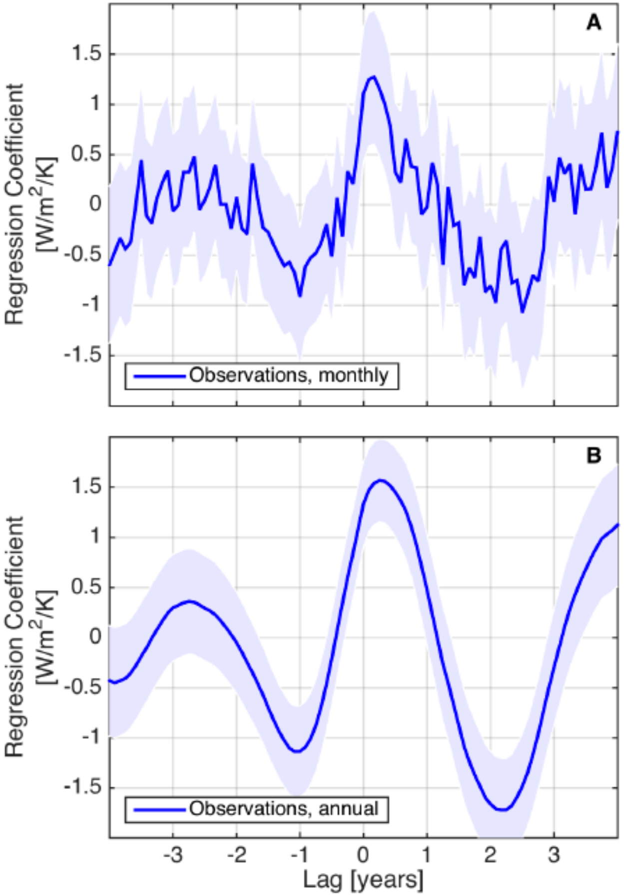




Regressing **monthly** data w/ 4 month lag implies ECS = 2.4 K (1.6-4.2K, 5-95%)

(Forster & Gregory 2006, Murphy 2009, Trenberth et al 2010, Dessler 2010, Donohoe et al 2014, Zhou et al 2015)

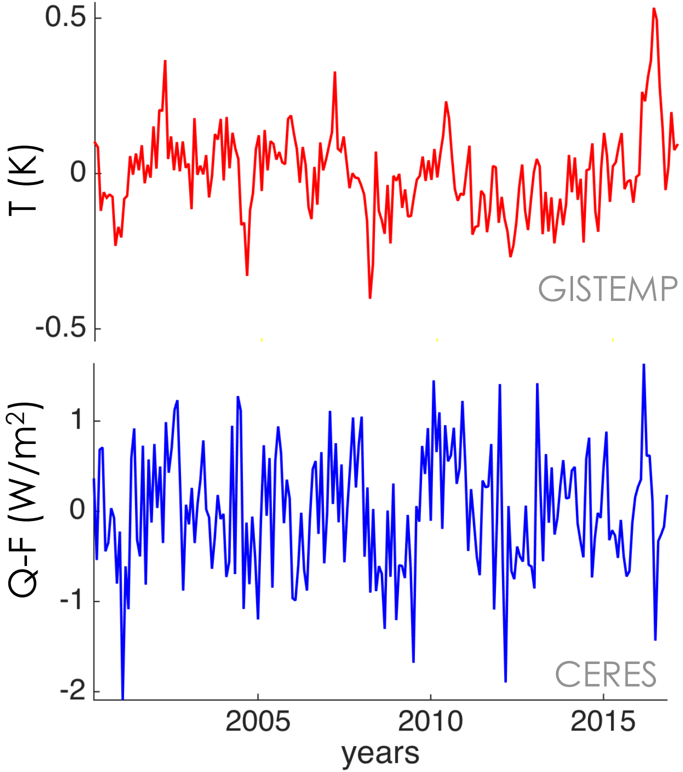
Lagged-regression structure between Q and T



Feedback estimate sensitive to choice of:

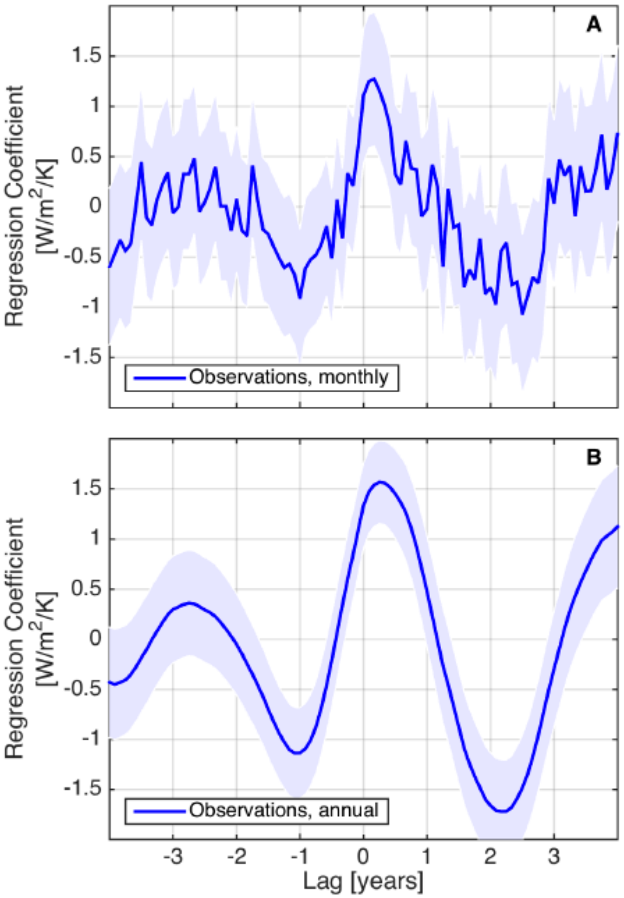
- lag
- averaging period
- record length

(Forster 2016)



(Forster & Gregory 2006, Murphy 2009, Trenberth et al 2010, Dessler 2010, Donohoe et al 2014, Zhou et al 2015)

Lagged-regression structure between Q and T

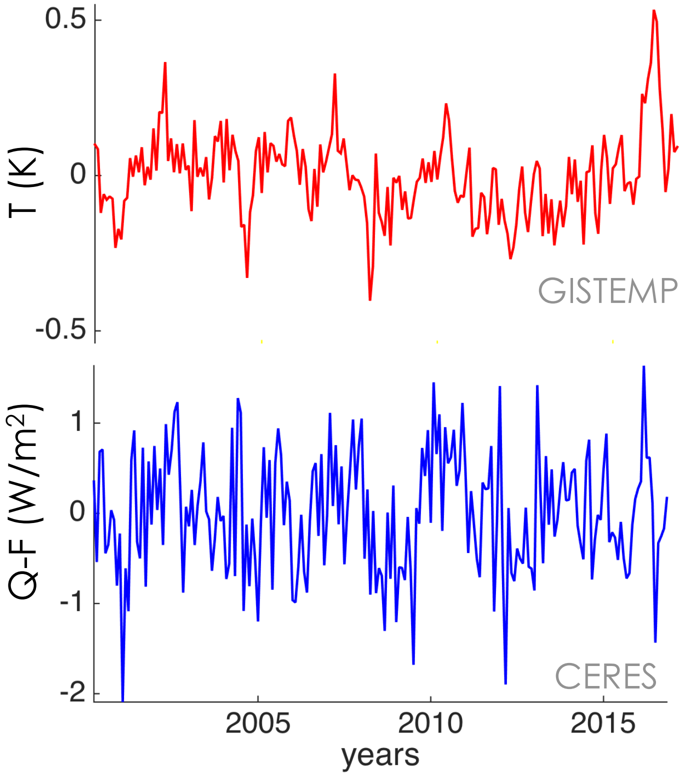


Feedback estimate sensitive to choice of:

- lag
- averaging period
- record length

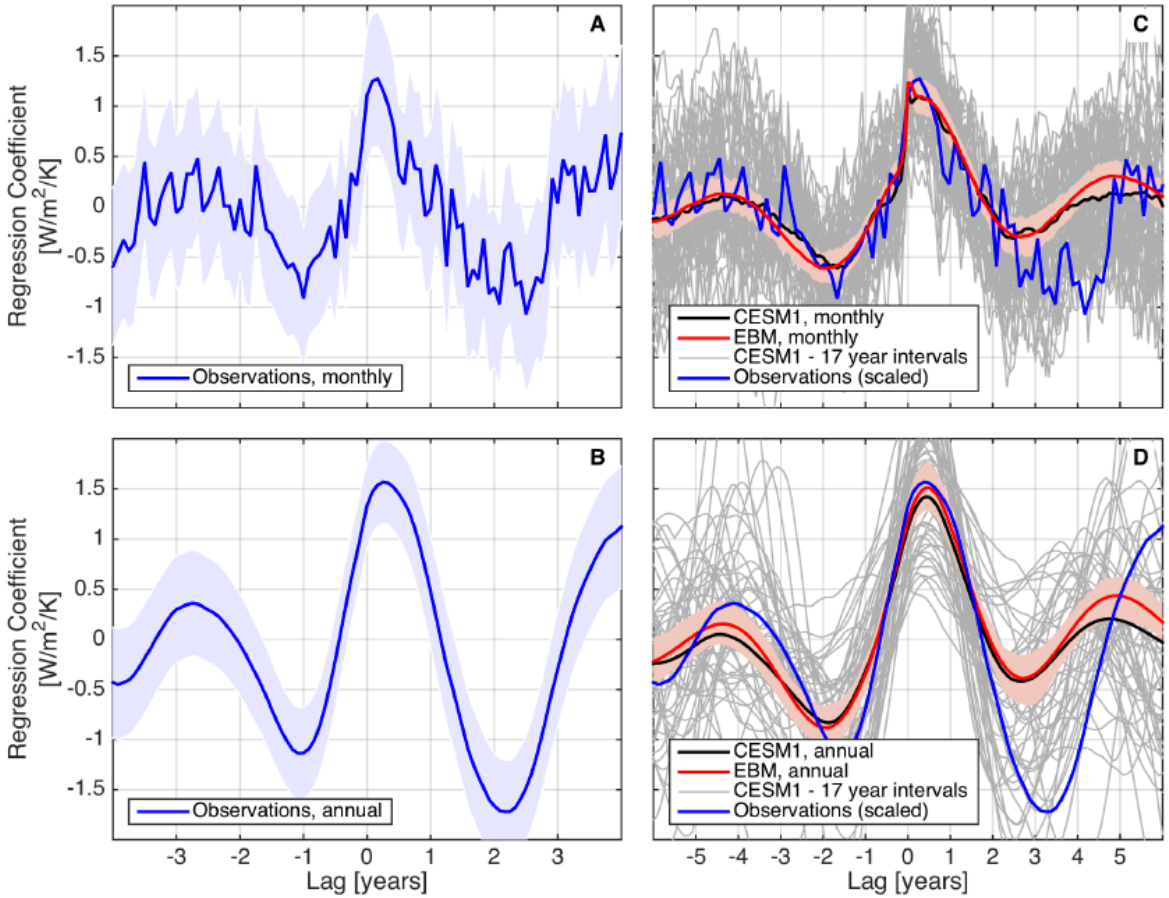
(Forster 2016)

Feedback value depends on source of stochastic forcing (oceanic vs radiative)
(Spencer & Braswell 2010, 2011; Dessler 2011)



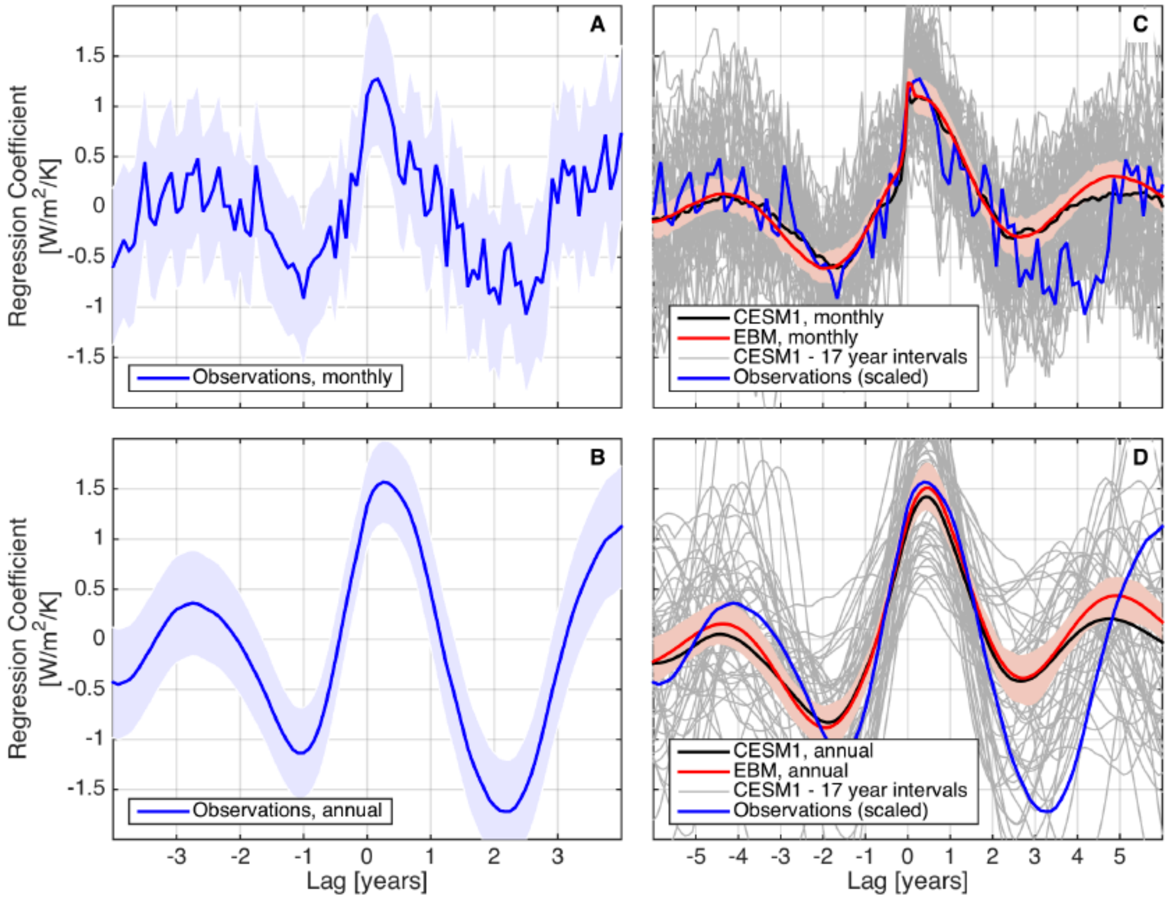
(Forster & Gregory 2006, Murphy 2009, Trenberth et al 2010, Dessler 2010, Donohoe et al 2014, Zhou et al 2015)

Using models to understand regression structure



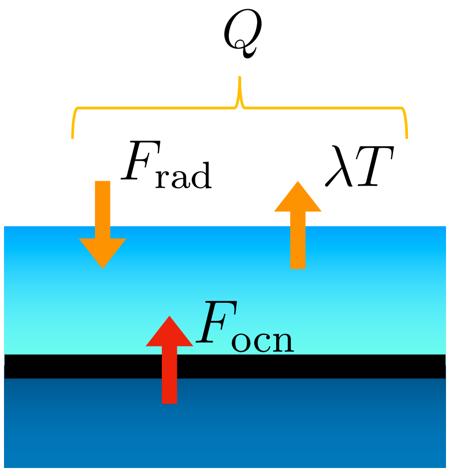
- Long pre-industrial unforced control simulation of NCAR's Community Earth System Model (CESM1) reproduces the salient features of observed regression structure with feedback dependence on:
  - lag
  - averaging period

Using models to understand regression structure



- Long pre-industrial unforced control simulation of NCAR's Community Earth System Model (CESM1) reproduces the salient features of observed regression structure with feedback dependence on:
  - lag
  - averaging period
- Suggests that observed regression structure mainly reflects internal variability
- We can use models to understand the regression structure

Intuition from a Hasselmann Model

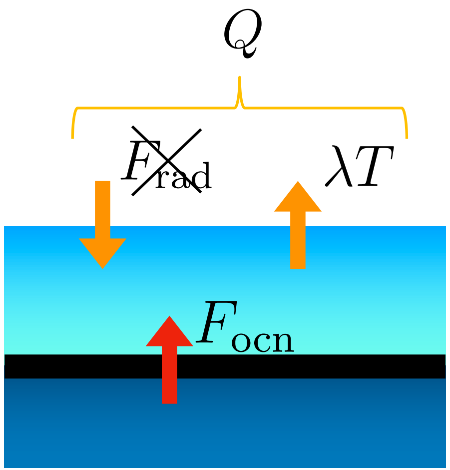


$$C\frac{dT}{dt} = \underbrace{\lambda T + F_{\text{rad}}}_{Q} + F_{\text{ocn}}$$

white noise
radiative forcing

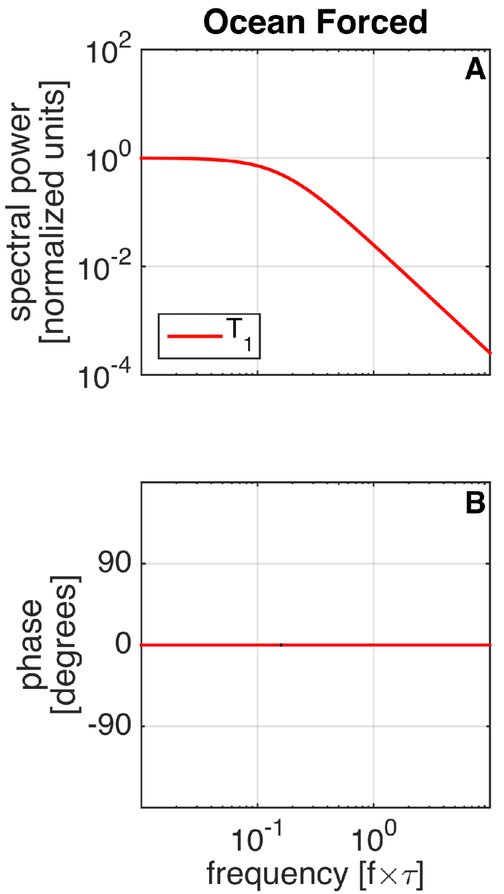
white noise
ocean forcing

Intuition from a Hasselmann Model

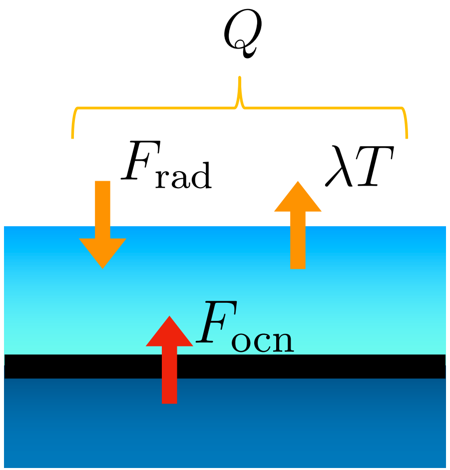


$$C\frac{dT}{dt} = \underbrace{\lambda T + \cancel{F_{\mathrm{rad}}}}_{Q} + F_{\mathrm{ocn}}$$

$Q = \lambda T$ (in phase)

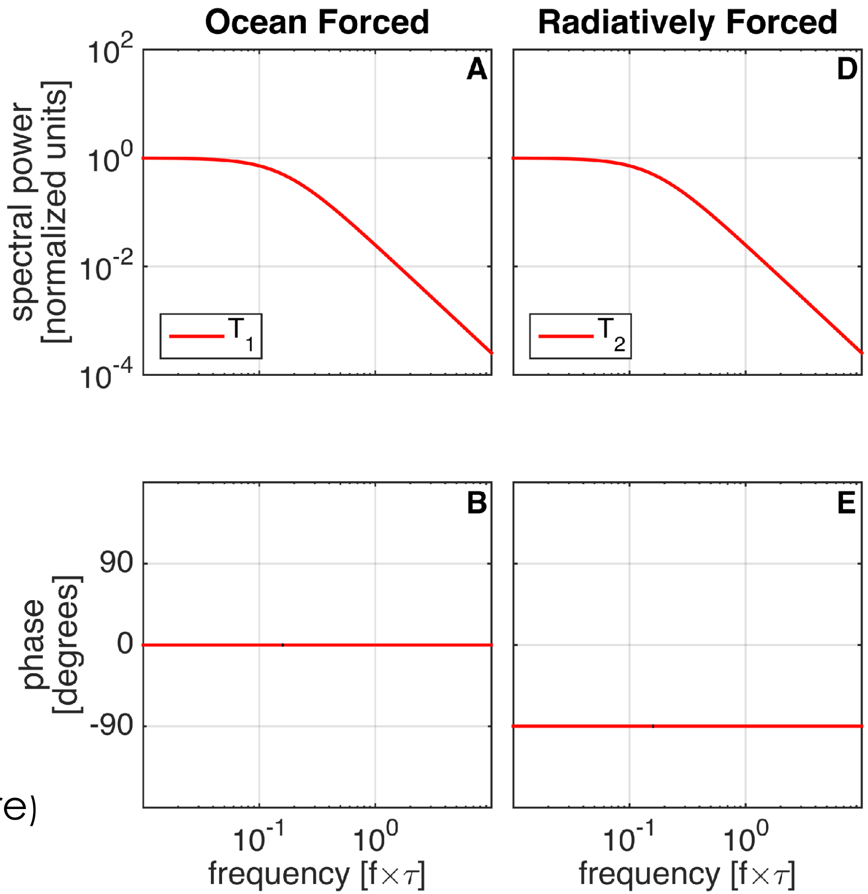


Intuition from a Hasselmann Model

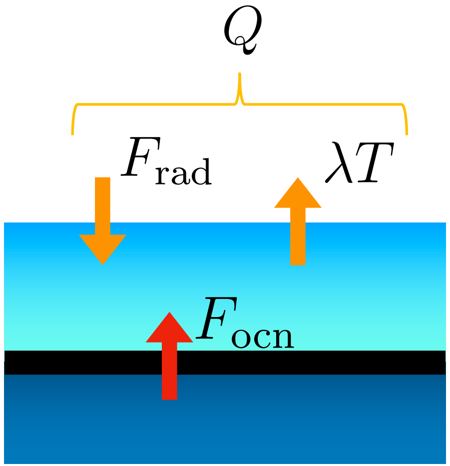


$$C\frac{dT}{dt} = \underbrace{\lambda T + F_{\text{rad}}}_{Q} + \cancel{F_{\text{ocn}}}$$

$$Q = C\frac{dT}{dt}$$ (in quadrature)

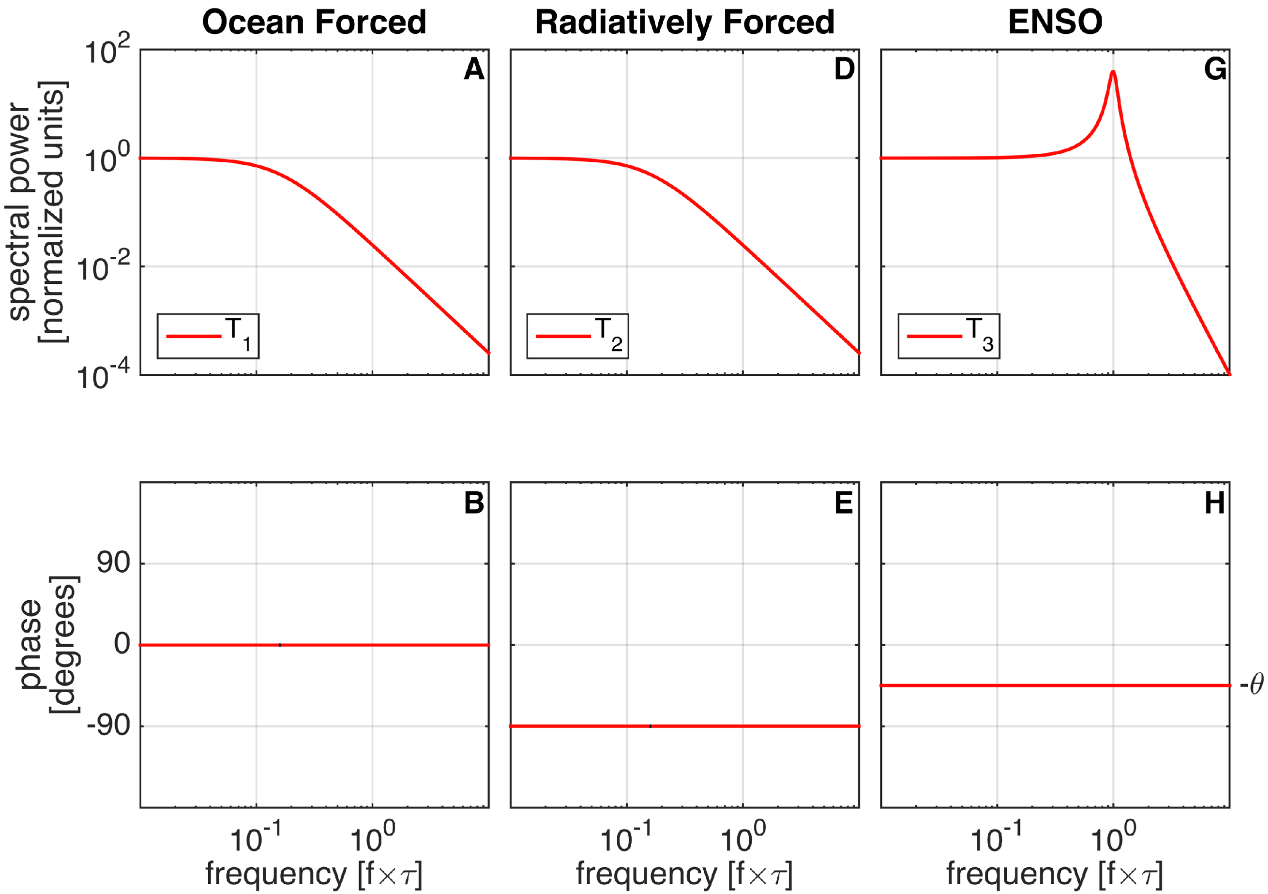


Intuition from a Hasselmann Model

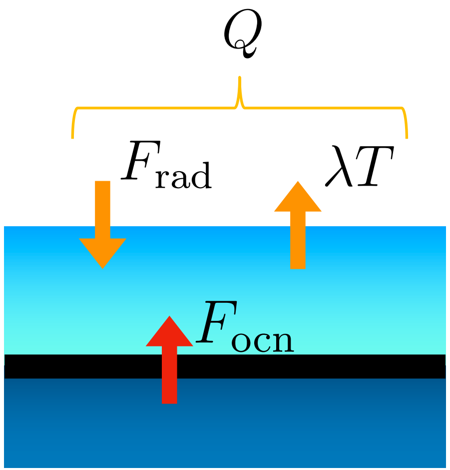


$$C\frac{dT}{dt} = \underbrace{\lambda T + F_{\mathrm{rad}}}_{Q} + F_{\mathrm{ocn}}$$

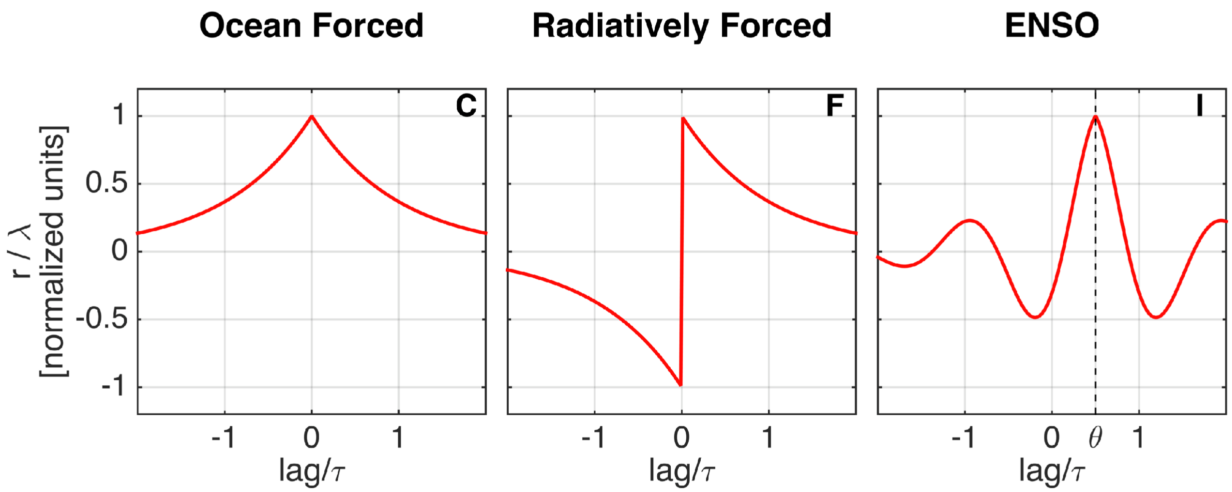
$$Q(t) = \lambda T(t - \theta)$$



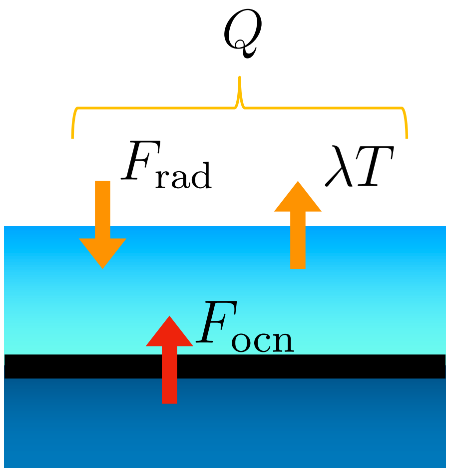
Intuition from a Hasselmann Model

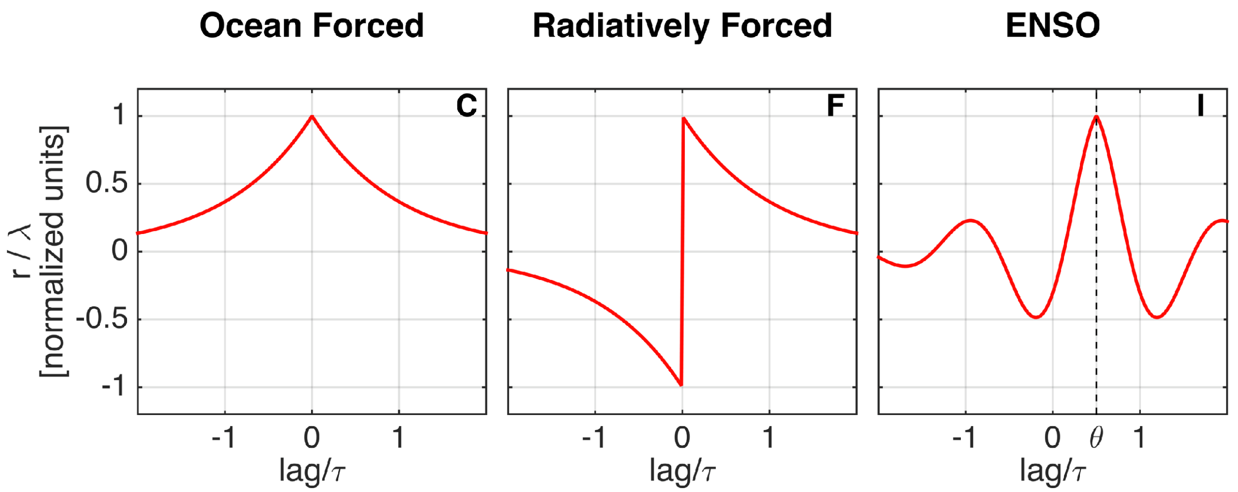


$$C\frac{dT}{dt} = \underbrace{\lambda T + F_{\mathrm{rad}}}_{Q} + F_{\mathrm{ocn}}$$



Intuition from a Hasselmann Model





$$C\frac{dT}{dt} = \underbrace{\lambda T + F_{\mathrm{rad}}}_{Q} + F_{\mathrm{ocn}}$$

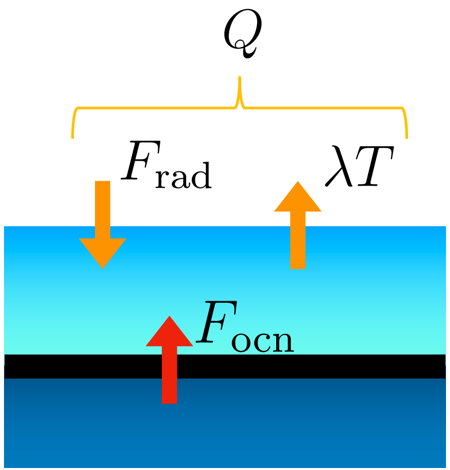
- Will each type of forcing engender the same radiative feedback? For this we need global climate models

CESM1 model hierarchy

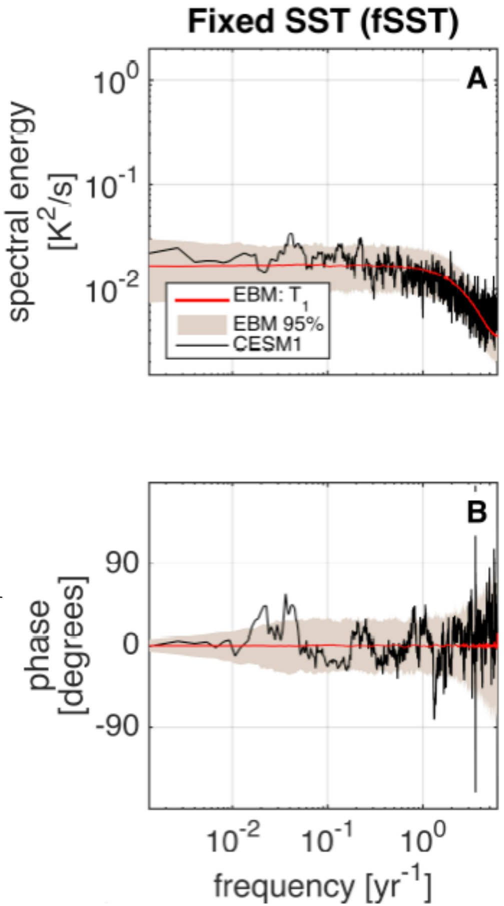
- Consider a hierarchy of CESM1 pre-industrial unforced control simulations

• OCN: CAM5 w/dynamic ocean (CESM1)	Atmosphere(**Y**), Slab(**Y**), ENSO(**Y**)
• SOM: CAM5 w/thermodynamic slab ocean	Atmosphere(**Y**), Slab(**Y**), ENSO(**N**)
• fSST: CAM5 w/fixed sea-surface temperatures	Atmosphere(**Y**), Slab(**N**), ENSO(**N**)

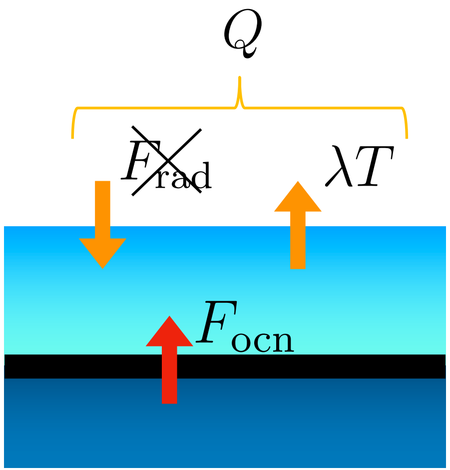
Fixed SST simulation



$$C\frac{dT}{dt} = \underbrace{\lambda T + F_{\mathrm{rad}}}_{Q} + F_{\mathrm{ocn}}$$

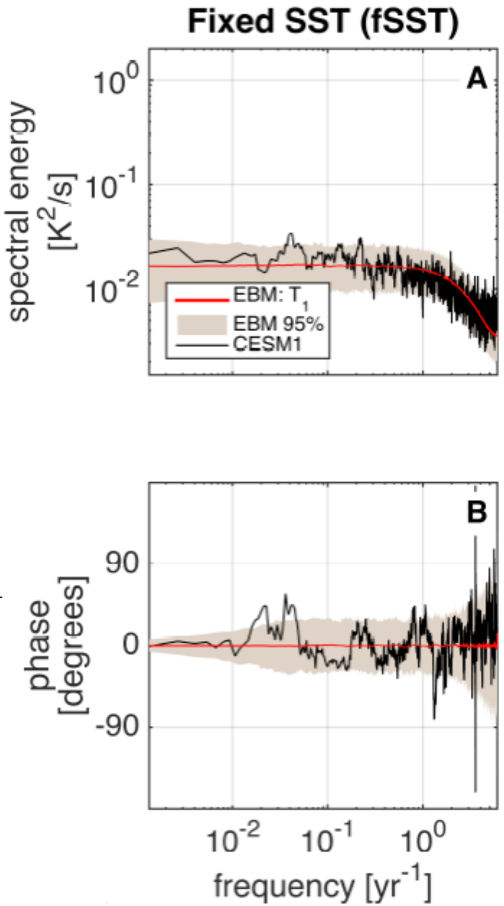


Fixed SST simulation



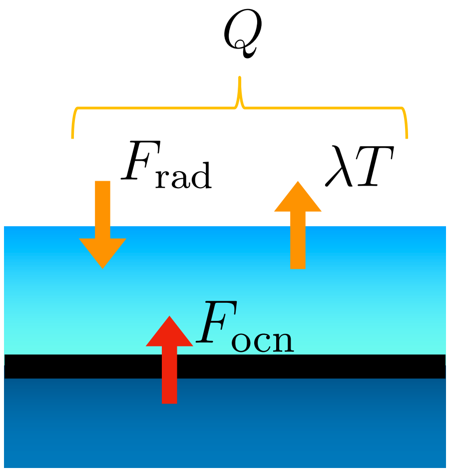
$$C\frac{dT}{dt} = \underbrace{\lambda T + \cancel{F_{\text{rad}}}}_{Q} + F_{\text{ocn}}$$

$Q = \lambda T$ (in phase)

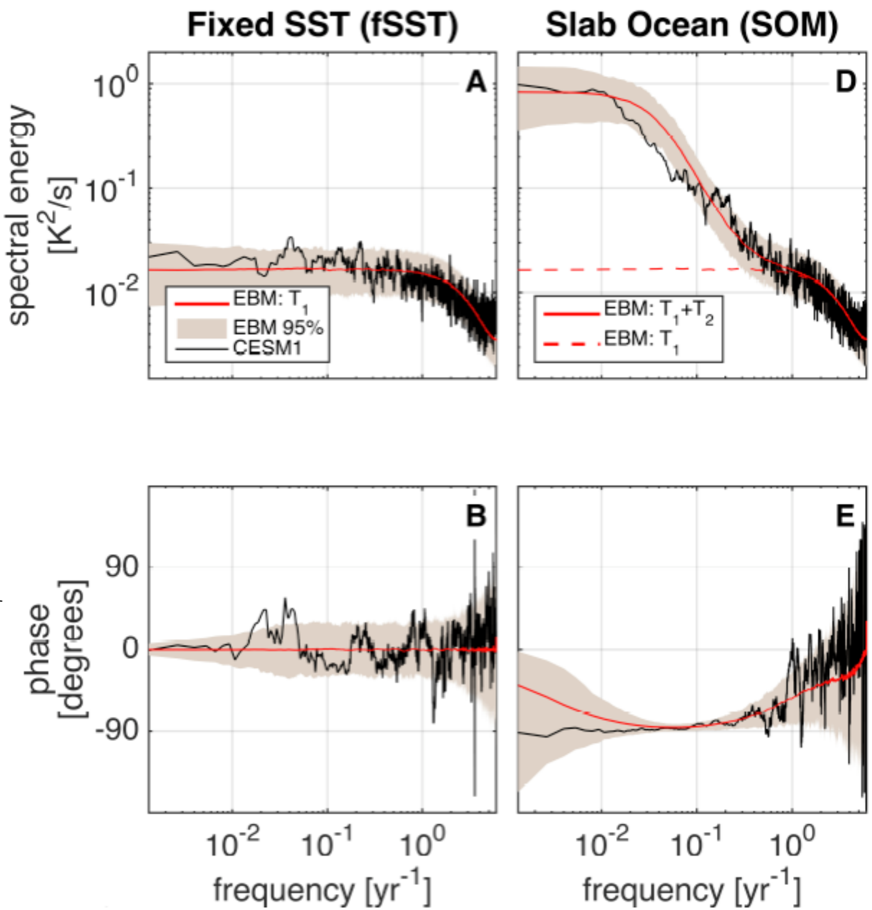


- Note: Stochastic forcing comes from wind variability extracting energy from the ocean through turbulent fluxes (an ocean forcing); air temperature is strongly damped by turbulent heat fluxes

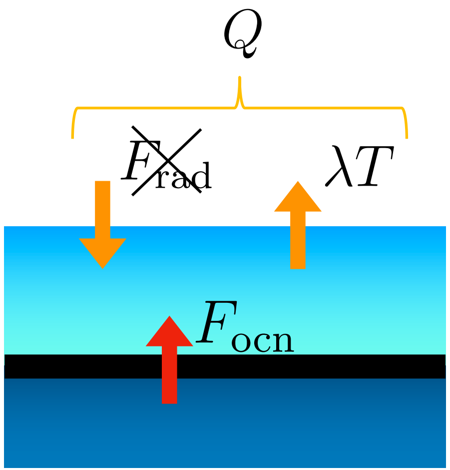
Slab ocean model simulation



$$C\frac{dT}{dt} = \underbrace{\lambda T + F_{\mathrm{rad}}}_{Q} + F_{\mathrm{ocn}}$$

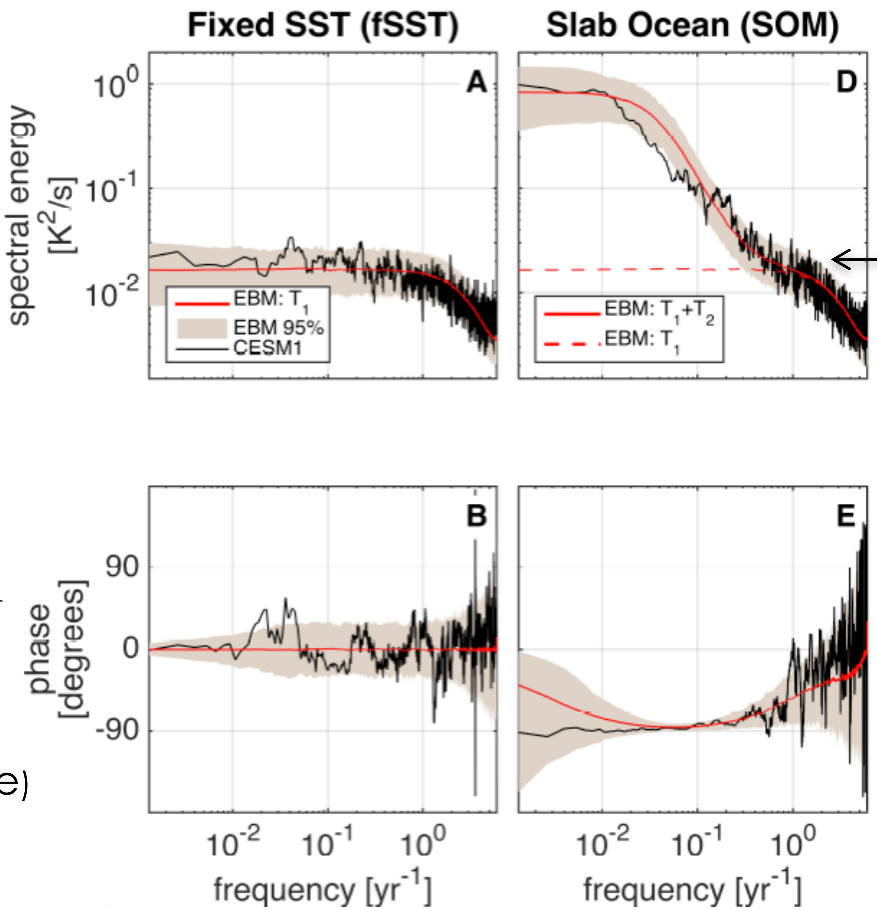


Slab ocean model simulation



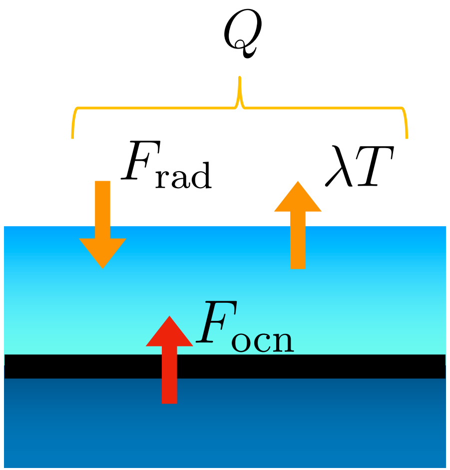
$$C\frac{dT}{dt} = \underbrace{\lambda T + \cancel{F_{\rm rad}}}_{Q} + F_{\rm ocn}$$

High freq: $Q = \lambda T$ (in phase)



Fast mode with λ_1

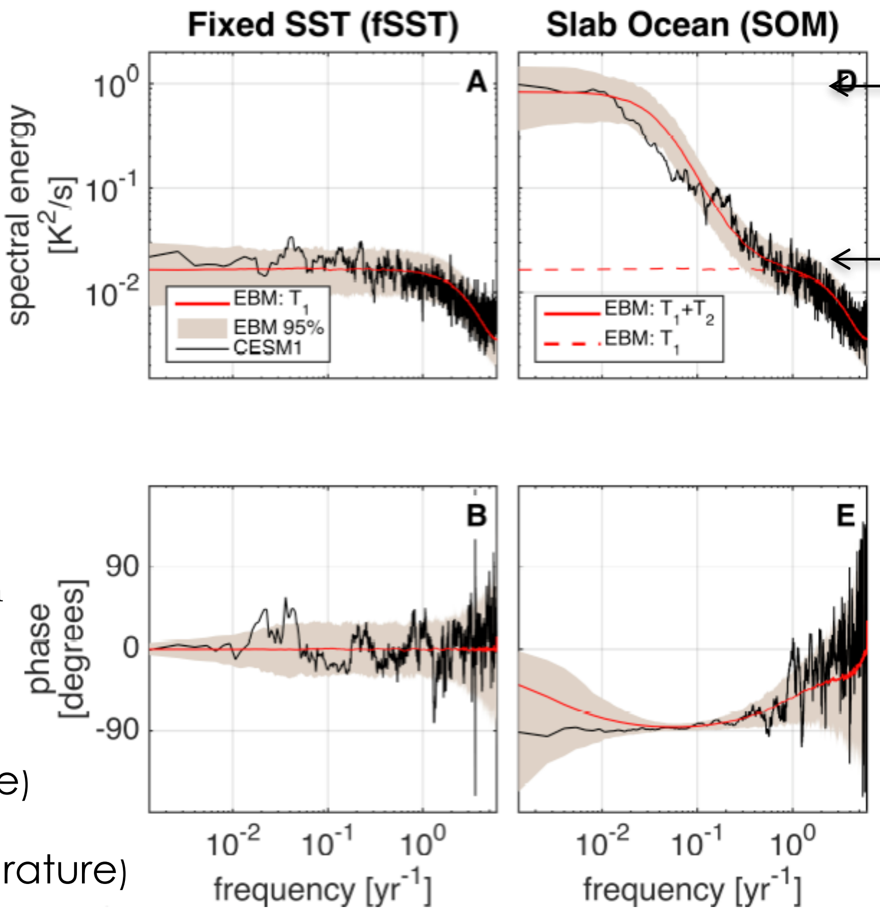
Slab ocean model simulation



$$C\frac{dT}{dt} = \underbrace{\lambda T + F_{\mathrm{rad}}}_{Q} + \cancel{F_{\mathrm{ocn}}}$$

High freq: $Q = \lambda T$ (in phase)

Low freq: $Q = C\frac{dT}{dt}$ (in quadrature)

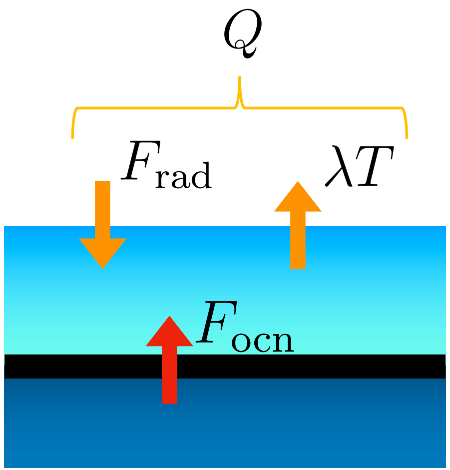


Slow mode with λ_2

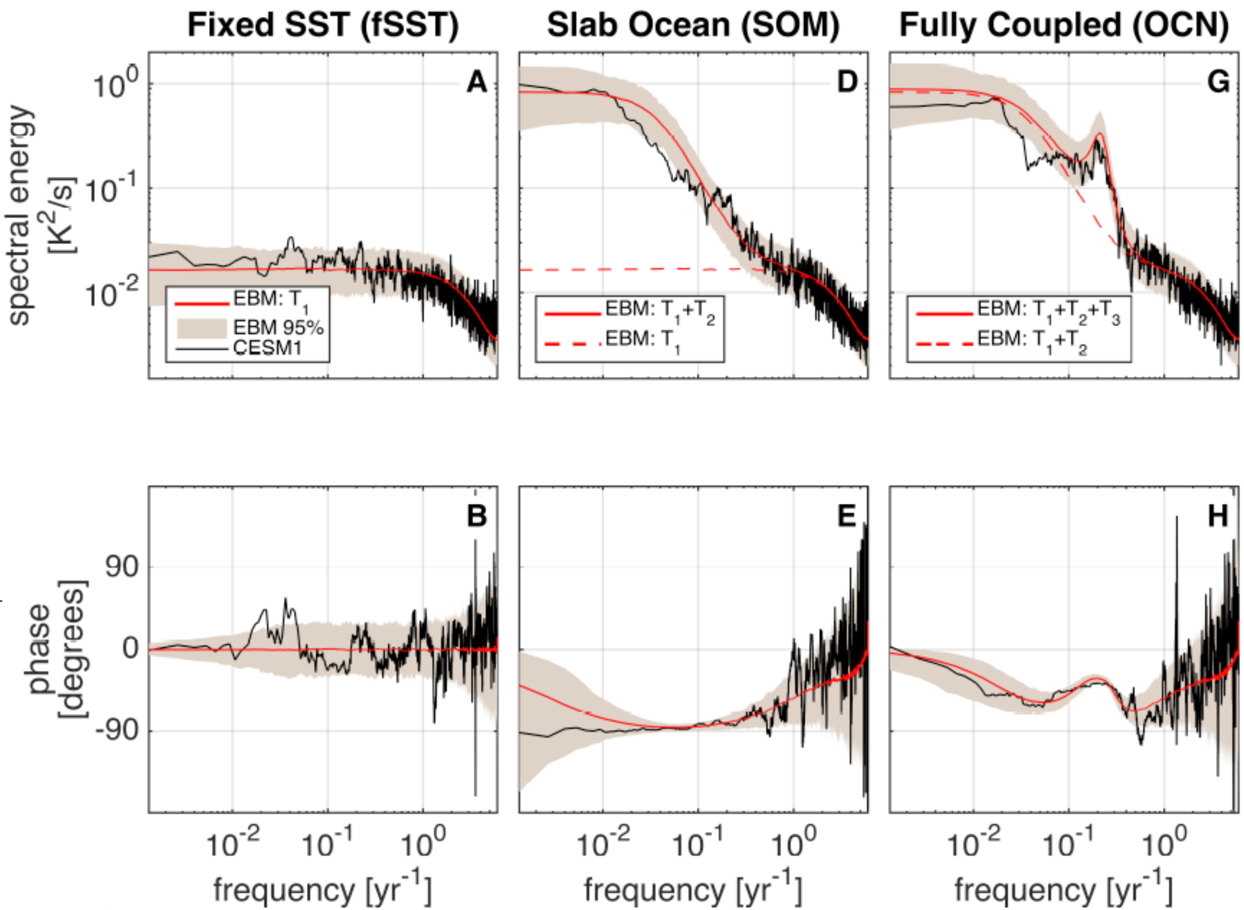
Fast mode with λ_1

- Note: Stochastic forcing for the "slow" mode comes from radiation, leading to different feedback estimate; air temperature is weakly radiatively damped

Fully-coupled CESM1 simulation



$$C\frac{dT}{dt} = \underbrace{\lambda T + F_{\mathrm{rad}}}_{Q} + F_{\mathrm{ocn}}$$

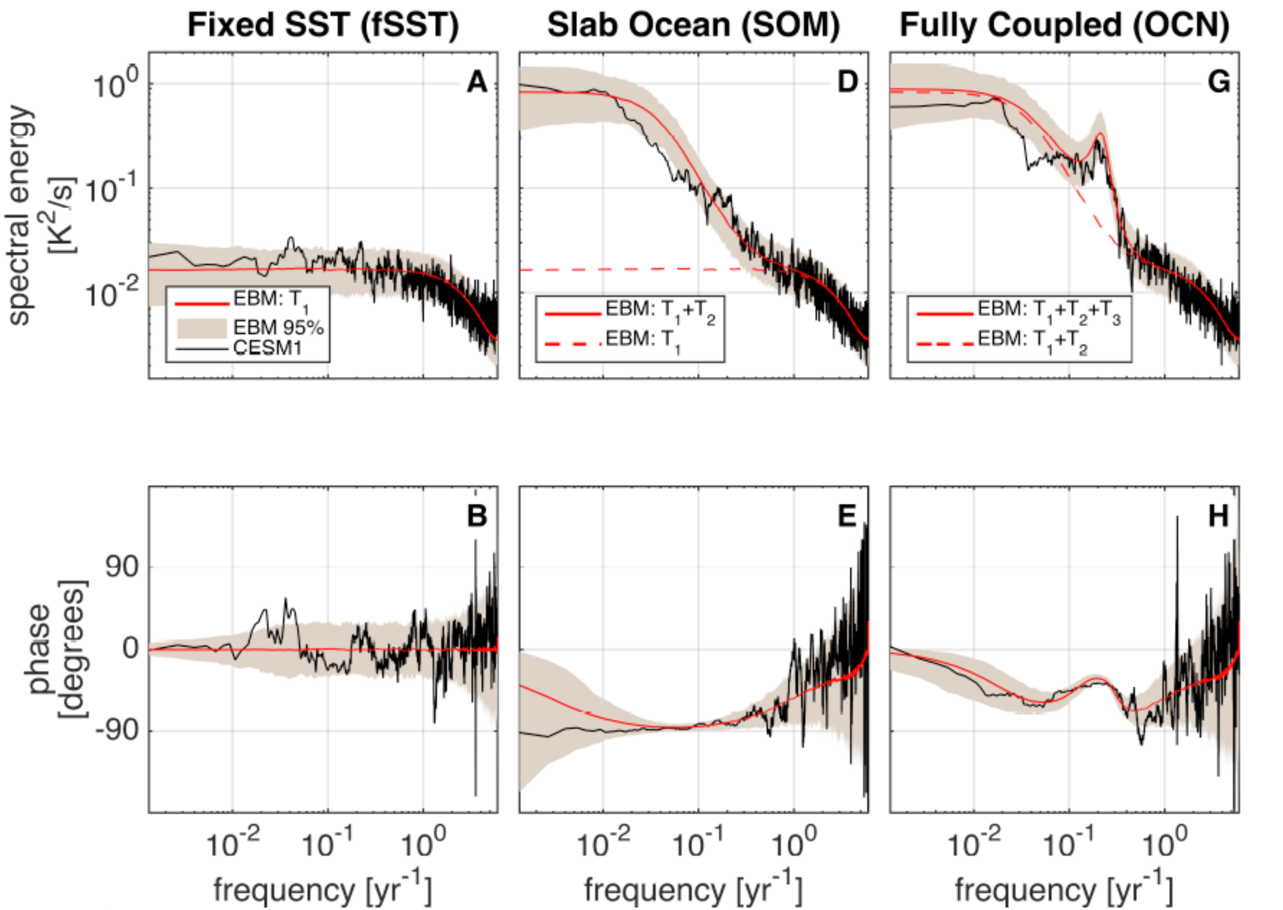


Modeling the lagged-regression

Stochastic linear energy balance model (EBM):

- Fit to individual simulations (fSST, SOM, ENSO band) sums linearly to capture fully-coupled simulation

- Can be solved analytically to understand lagged-regression structure



Modeling the lagged-regression

Stochastic linear energy balance model (EBM):

- Fit to individual simulations (fSST, SOM, ENSO band) sums linearly to capture fully-coupled simulation

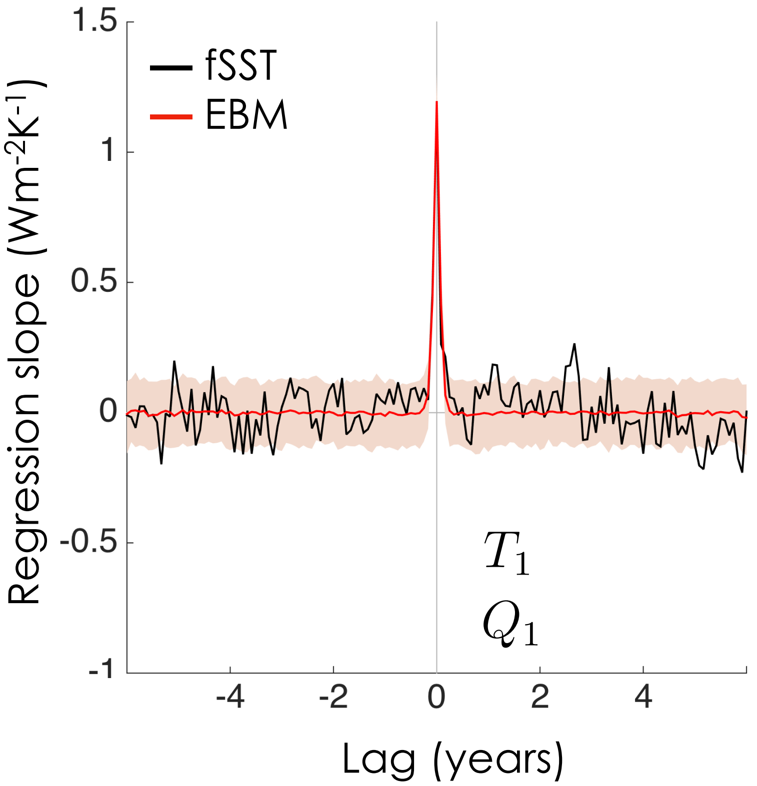
- Can be solved analytically to understand lagged-regression structure

$$\boxed{r(\mathrm{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\mathrm{total}}} \right) \mathrm{acf}(\mathrm{lag})}$$

Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

Fixed SST simulation



$$r(\text{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\text{total}}} \right) \text{acf}(\text{lag})$$

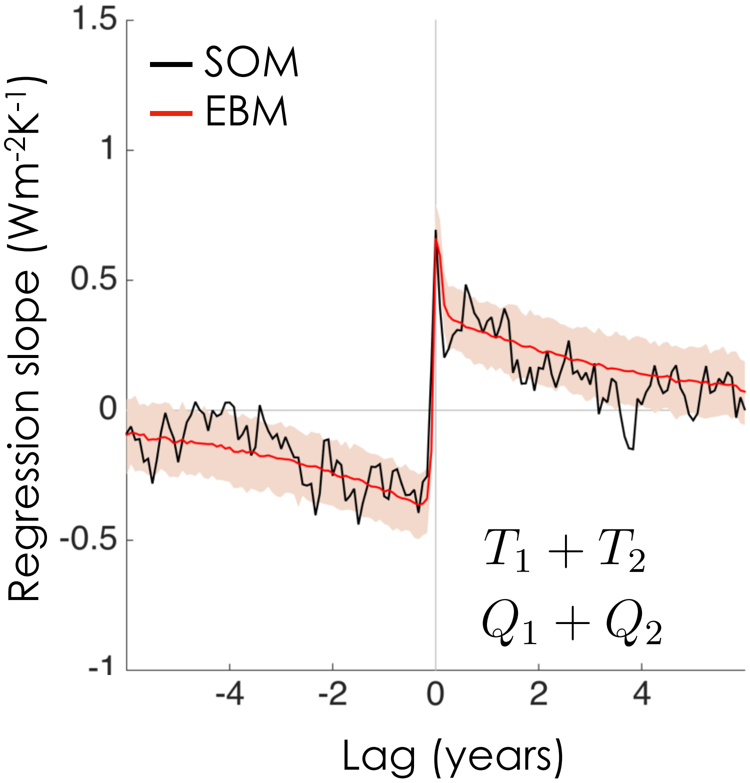
Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

Fixed SST has single mode:

$$Q_1 = \lambda_1 T_1$$

Slab ocean model simulation



$$r(\text{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\text{total}}} \right) \text{acf}(\text{lag})$$

Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

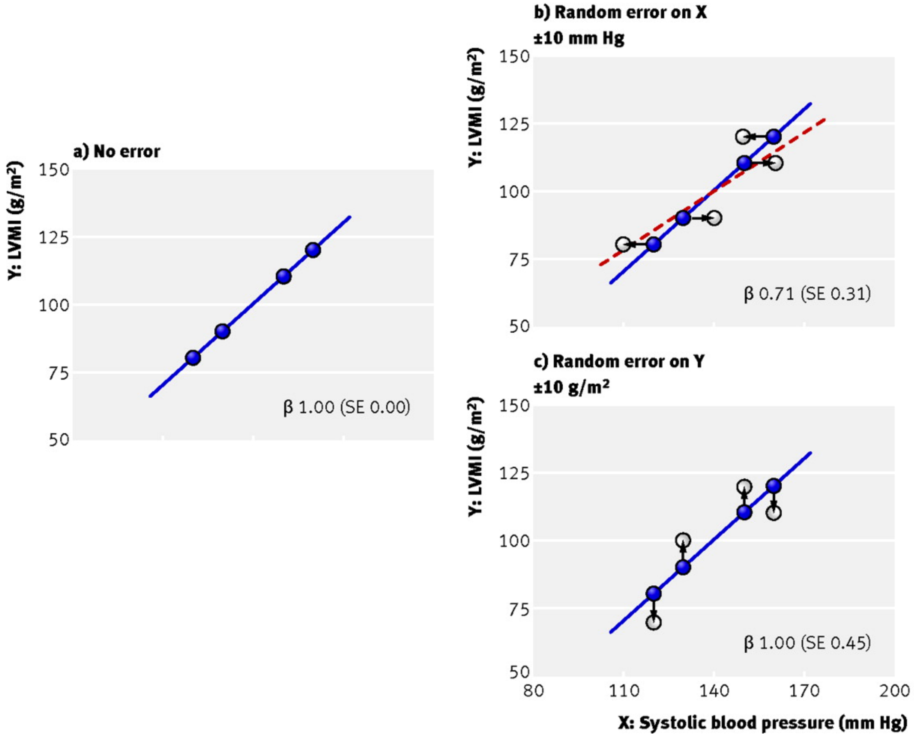
Slab ocean is sum of two modes:

$$Q_1 = \lambda_1 T_1$$
$$Q_2 = \lambda_2 T_2 + F_{\text{rad}} \propto \frac{dT_2}{dt}$$

Regression dilution

- Temperature variance in one mode biases regression estimates for all (regression dilution)

$$r(\mathrm{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\mathrm{total}}} \right) \mathrm{acf}(\mathrm{lag})$$



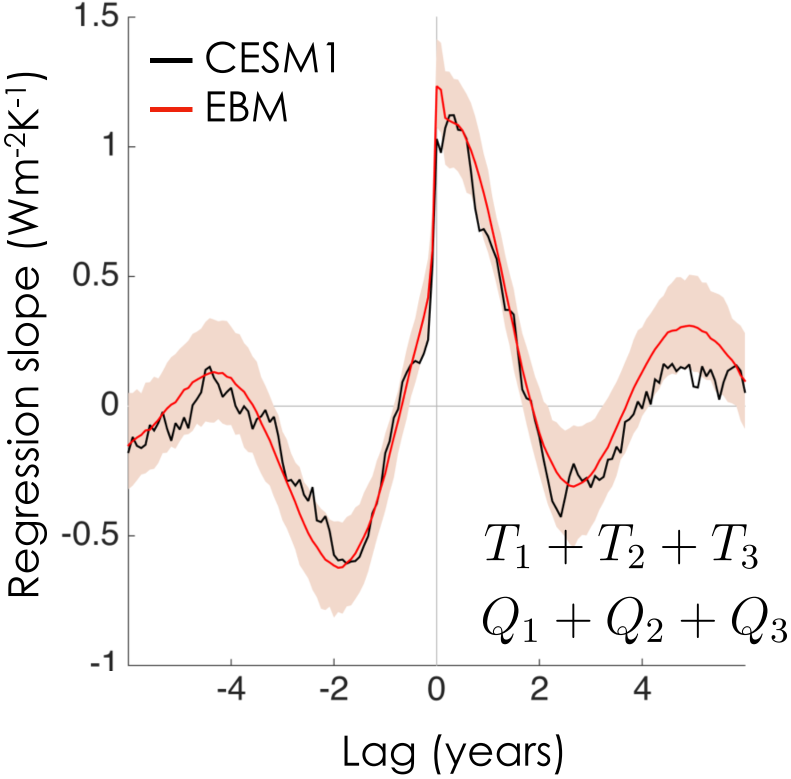
Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

Slab ocean is sum of two modes:

$$Q_1 = \lambda_1 T_1$$
$$Q_2 = \lambda_2 T_2 + F_{\mathrm{rad}} \propto \frac{dT_2}{dt}$$

Fully-coupled model simulation



$$r(\text{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\text{total}}} \right) \text{acf}(\text{lag})$$

Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

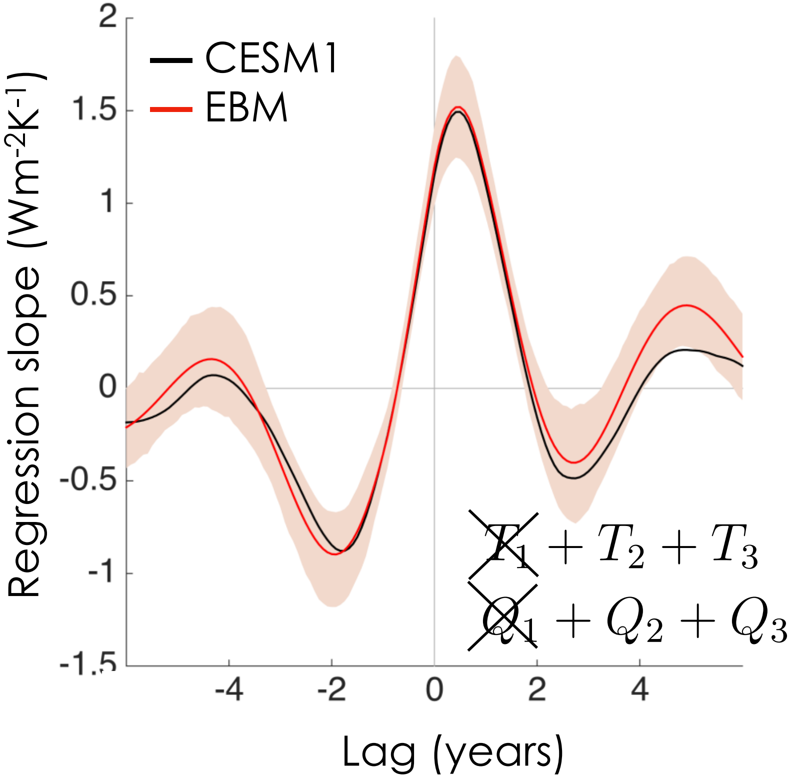
Fully-coupled model is sum of (at least) three modes:

$$Q_1 = \lambda_1 T_1$$

$$Q_2 = \lambda_2 T_2 + F_{\text{rad}} \propto \frac{dT_2}{dt}$$

$$Q_3(t) = \lambda_3 T_3(t - \theta) \quad \text{(ENSO)}$$

Fully-coupled model simulation

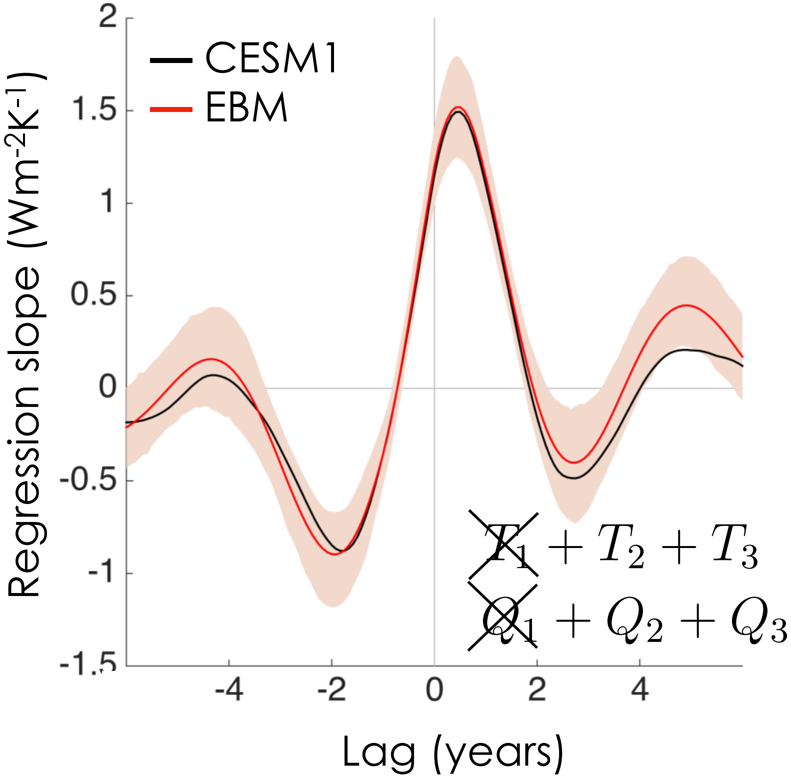


$$r(\text{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\text{total}}} \right) \text{acf}(\text{lag})$$

Regression slope at a given lag is:
- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

Annual averaging preferentially eliminates fast, air-sea interaction mode

Fully-coupled model simulation



$$r(\mathrm{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\mathrm{total}}} \right) \mathrm{acf}(\mathrm{lag})$$

Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

While dynamics are well separated by time-scale, variance and covariance (regression) amalgamate across time scales

Changing fractional variances & acf explains regression sensitivity to lag and sampling

Fully-coupled model simulation

CESM1 feedbacks
($Wm^{-2}K^{-1}$)

Air-sea forced	$\lambda_1 = 1.2$
Radiatively forced	$\lambda_2 = 0.9$
ENSO	$\lambda_3 = 3.0$

$$r(\text{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\text{total}}} \right) \text{acf}(\text{lag})$$

Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

While dynamics are well separated by time-scale, variance and covariance (regression) amalgamate across time scales

Changing fractional variances & acf explains regression sensitivity to lag and sampling

Fully-coupled model simulation

CESM1 feedbacks
($Wm^{-2}K^{-1}$)

Air-sea forced	$\lambda_1 = 1.2$
Radiatively forced	$\lambda_2 = 0.9$
ENSO	$\lambda_3 = 3.0$
Zero-lag regression	$r(0) = 1.2$
Peak regression (NOT ENSO!)	$r(\theta) = 1.0$

$$\boxed{r(\text{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\text{total}}} \right) \text{acf}(\text{lag})}$$

Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

While dynamics are well separated by time-scale, variance and covariance (regression) amalgamate across time scales

Changing fractional variances & acf explains regression sensitivity to lag and sampling

Fully-coupled model simulation

CESM1 feedbacks
($Wm^{-2}K^{-1}$)

Air-sea forced	$\lambda_1 = 1.2$
Radiatively forced	$\lambda_2 = 0.9$
ENSO	$\lambda_3 = 3.0$
Zero-lag regression	$r(0) = 1.2$
Peak regression (NOT ENSO!)	$r(\theta) = 1.0$
Global warming	$\lambda_{\mathrm{GHG}} = 0.9$

$$r(\mathrm{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\mathrm{total}}}\right) \mathrm{acf}(\mathrm{lag})$$

Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

While dynamics are well separated by time-scale, variance and covariance (regression) amalgamate across time scales

Changing fractional variances & acf explains regression sensitivity to lag and sampling

Fully-coupled model simulation

	CESM1 feedbacks ($Wm^{-2}K^{-1}$)	CCSM4 feedbacks ($Wm^{-2}K^{-1}$)
Air-sea forced	$\lambda_1 = 1.2$	$\lambda_1 = 1.5$
Radiatively forced	$\lambda_2 = 0.9$	$\lambda_2 = 1.5$
ENSO	$\lambda_3 = 3.0$	$\lambda_3 = 2.2$
Zero-lag regression	$r(0) = 1.2$	$r(0) = 1.2$
Peak regression (NOT ENSO!)	$r(\theta) = 1.0$	$r(\theta) = 1.1$
Global warming	$\lambda_{\mathrm{GHG}} = 0.9$	$\lambda_{\mathrm{GHG}} = 1.3$

$$r(\mathrm{lag}) = \sum \lambda_i \left(\frac{\sigma_{T_i}}{\sigma_{\mathrm{total}}} \right) \mathrm{acf}(\mathrm{lag})$$

Regression slope at a given lag is:

- average of distinct feedbacks of different modes
- weighted by relative variance of each mode
- weighted by autocorrelation of each mode at the given lag

While dynamics are well separated by time-scale, variance and covariance (regression) amalgamate across time scales

Changing fractional variances & acf explains regression sensitivity to lag and sampling

Thoughts regarding Method #1

- Lagged regression between TOA radiation and surface temperature can be understood as a superposition of linear modes, each with a distinct radiative feedback

Thoughts regarding Method #1

- Lagged regression between TOA radiation and surface temperature can be understood as a superposition of linear modes, each with a distinct radiative feedback

- Regression slope at a given lag is:
  - average of distinct feedbacks of different modes
  - weighted by relative variance of each mode
  - weighted by autocorrelation of each mode at the given lag

Thoughts regarding Method #1

- Lagged regression between TOA radiation and surface temperature can be understood as a superposition of linear modes, each with a distinct radiative feedback

- Regression slope at a given lag is:
    - average of distinct feedbacks of different modes
    - weighted by relative variance of each mode
    - weighted by autocorrelation of each mode at the given lag

- Regression slope is sensitive to lag and averaging period, and should not be expected to give an estimate of long-term feedback

Thoughts regarding Method #1

- Lagged regression between TOA radiation and surface temperature can be understood as a superposition of linear modes, each with a distinct radiative feedback

- Regression slope at a given lag is:
  - average of distinct feedbacks of different modes
  - weighted by relative variance of each mode
  - weighted by autocorrelation of each mode at the given lag

- Regression slope is sensitive to lag and averaging period, and should not be expected to give an estimate of long-term feedback

- Ongoing work:
  - can feedbacks of individual modes be derived from observations?
  - do any of the individual feedbacks correlate with long-term feedbacks across models? (potentially for an observational constraint on ECS)
  - for how long will we have to observe before forced feedbacks emerge above internal variability? (estimate from Cristi: minimum ~25 years)

Radiative feedbacks from stochastic variability in surface temperature and radiative imbalance

Cristian Proistosescu[1], Aaron Donohoe[2], Kyle C. Armour[3,4], Gerard H. Roe[5],

Malte F. Stuecker[4,6], Cecilia M. Bitz[4]

Online at *Geophysical Research Letters* as of yesterday

Estimating climate sensitivity should be easy... right?

- All we need to do is estimate the net radiative feedback λ

$$Q = \lambda T + F$$

  - Method #1: Get λ from regression of $Q - F$ against T over the CERES record
  - Method #2: $\lambda = \dfrac{\Delta Q - \Delta F}{\Delta T}$, where Δ represents a change relative to pre-industrial

Estimates of climate sensitivity

correspondence

Energy budget constraints on climate response

Alexander Otto[1*], Friederike E. L. Otto[1], Olivier Boucher[2], John Church[3], Gabi Hegerl[4], Piers M. Forster[5], Nathan P. Gillett[6], Jonathan Gregory[7], Gregory C. Johnson[8], Reto Knutti[9], Nicholas Lewis[10], Ulrike Lohmann[9], Jochem Marotzke[11], Gunnar Myhre[12], Drew Shindell[13], Bjorn Stevens[11] and Myles R. Allen[1,14]

$$\mathrm{ECS} = -\frac{F_{2\times}}{\lambda} = \frac{F_{2\times} T_{\mathrm{obs}}}{F_{\mathrm{obs}} - Q_{\mathrm{obs}}}$$

$$Q = \lambda T + F$$

T_{obs} = 0.75 ± 0.2 °C

Q_{obs} = 0.65 ± 0.27 Wm^{-2}

F_{obs} = 2.3 ± 1 Wm^{-2}

(years 2000-2009 relative to 1860-1879)

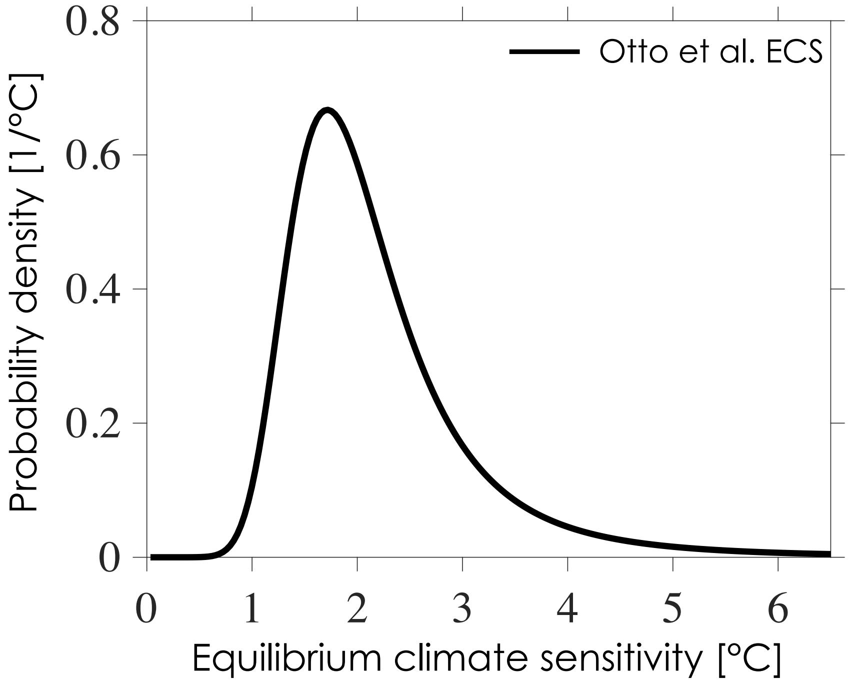
Estimates of climate sensitivity

correspondence

Energy budget constraints on climate response

Alexander Otto[1*], Friederike E. L. Otto[1], Olivier Boucher[2], John Church[3], Gabi Hegerl[4], Piers M. Forster[5], Nathan P. Gillett[6], Jonathan Gregory[7], Gregory C. Johnson[8], Reto Knutti[9], Nicholas Lewis[10], Ulrike Lohmann[9], Jochem Marotzke[11], Gunnar Myhre[12], Drew Shindell[13], Bjorn Stevens[11] and Myles R. Allen[1,14]

$$\mathrm{ECS} = -\frac{F_{2\times}}{\lambda} = \frac{F_{2\times} T_{\mathrm{obs}}}{F_{\mathrm{obs}} - Q_{\mathrm{obs}}}$$



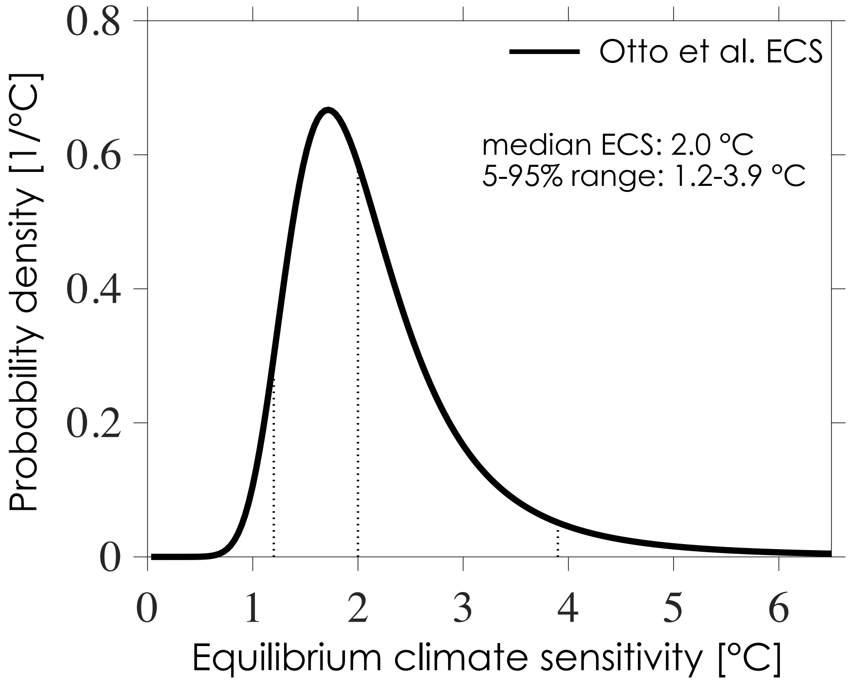
Estimates of climate sensitivity

correspondence

Energy budget constraints on climate response

Alexander Otto[1*], Friederike E. L. Otto[1], Olivier Boucher[2], John Church[3], Gabi Hegerl[4], Piers M. Forster[5], Nathan P. Gillett[6], Jonathan Gregory[7], Gregory C. Johnson[8], Reto Knutti[9], Nicholas Lewis[10], Ulrike Lohmann[9], Jochem Marotzke[11], Gunnar Myhre[12], Drew Shindell[13], Bjorn Stevens[11] and Myles R. Allen[1,14]

$$\mathrm{ECS} = -\frac{F_{2\times}}{\lambda} = \frac{F_{2\times} T_{\mathrm{obs}}}{F_{\mathrm{obs}} - Q_{\mathrm{obs}}}$$



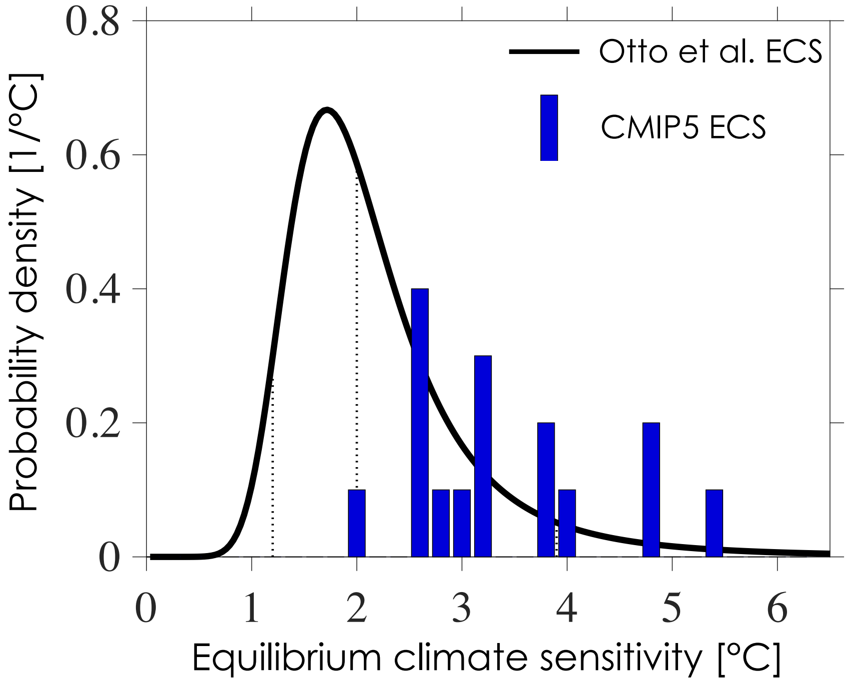
Estimates of climate sensitivity

correspondence

Energy budget constraints on climate response

Alexander Otto[1*], Friederike E. L. Otto[1], Olivier Boucher[2], John Church[3], Gabi Hegerl[4], Piers M. Forster[5], Nathan P. Gillett[6], Jonathan Gregory[7], Gregory C. Johnson[8], Reto Knutti[9], Nicholas Lewis[10], Ulrike Lohmann[9], Jochem Marotzke[11], Gunnar Myhre[12], Drew Shindell[13], Bjorn Stevens[11] and Myles R. Allen[1,14]

$$\mathrm{ECS} = -\frac{F_{2\times}}{\lambda} = \frac{F_{2\times} T_{\mathrm{obs}}}{F_{\mathrm{obs}} - Q_{\mathrm{obs}}}$$

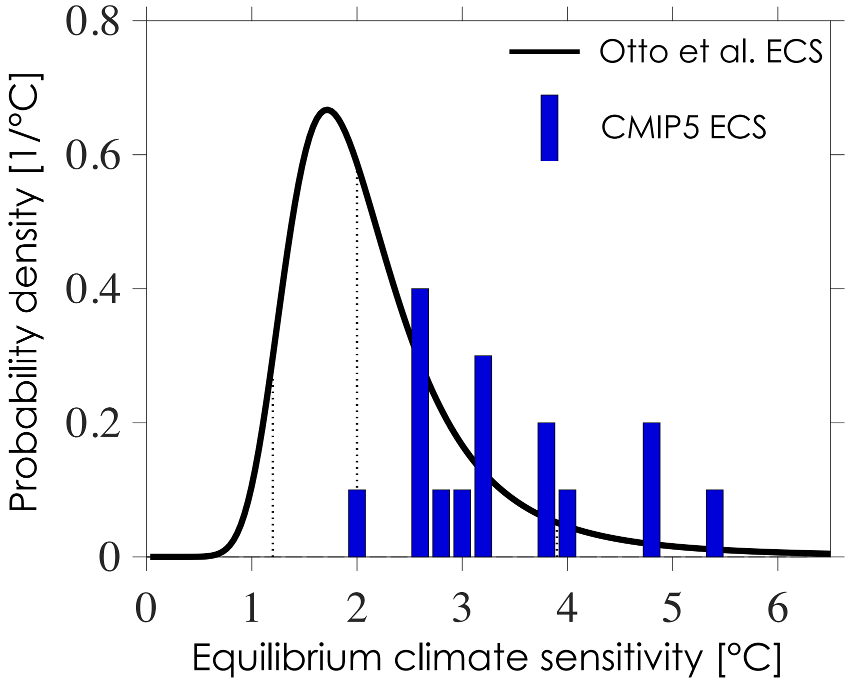


(Armour 2017; see also Proistosescu & Huybers 2017)

Estimates of climate sensitivity

- Global energy budget constraints produce estimates of ECS that are quite a bit lower than ECS simulated by CMIP5 models
  - Are the models overly sensitive?
  - Or is something else going on…?

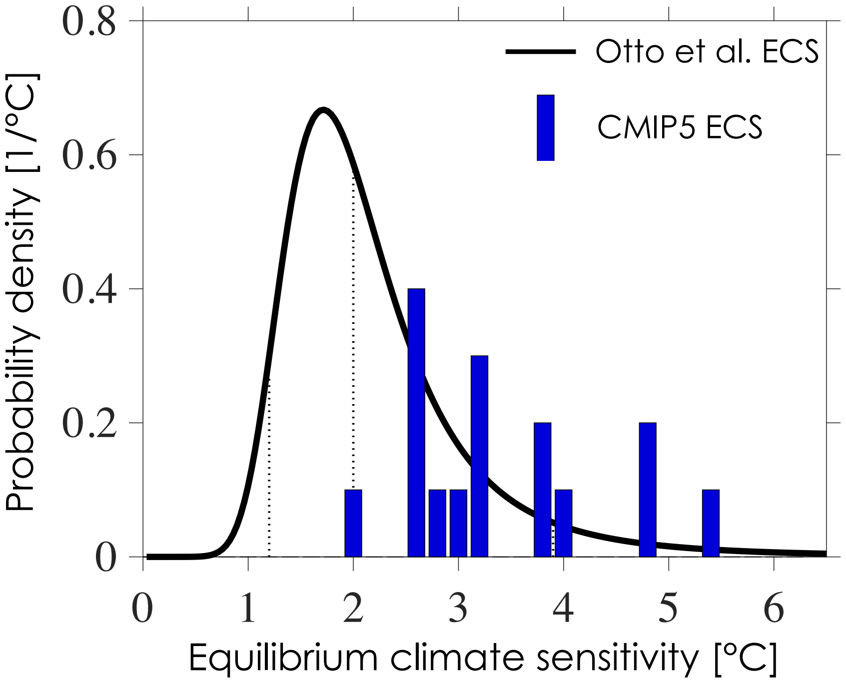
$$\mathrm{ECS} = -\frac{F_{2\times}}{\lambda}$$
$$= \frac{F_{2\times}T_{\mathrm{obs}}}{F_{\mathrm{obs}} - Q_{\mathrm{obs}}}$$



(Armour 2017; see also Proistosescu & Huybers 2017)

Like-with-like comparisons of climate sensitivity

- Emerging consensus: model-observational comparisons must be made in a *like-with-like* way

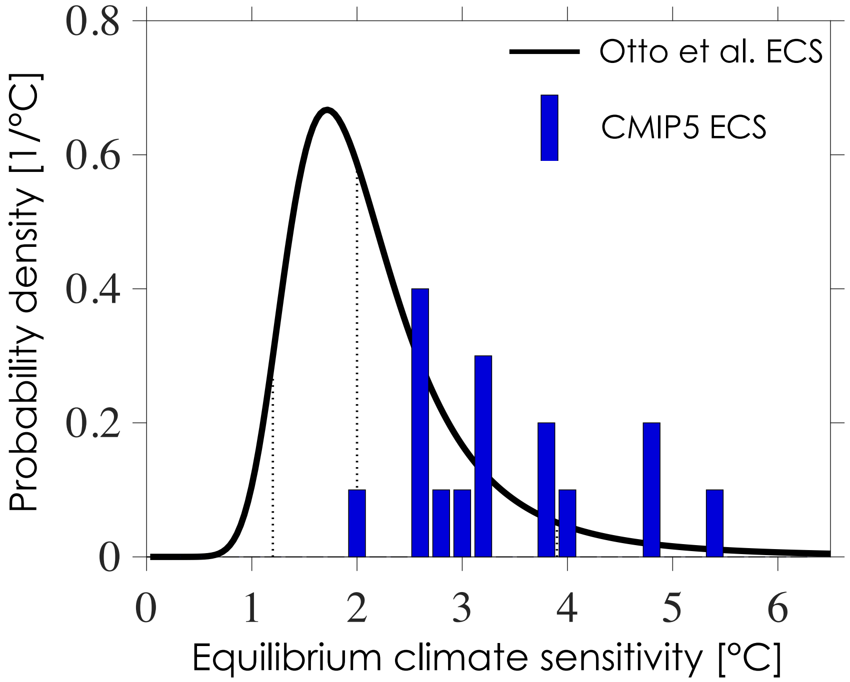


(Armour 2017; see also Proistosescu & Huybers 2017)

Like-with-like comparisons of climate sensitivity

- Emerging consensus: model-observational comparisons must be made in a *like-with-like* way, accounting for possibility that:

    1) Feedbacks (λ) vary over time as the spatial pattern of warming evolves (Armour 2017; Proistosescu & Huybers 2017)



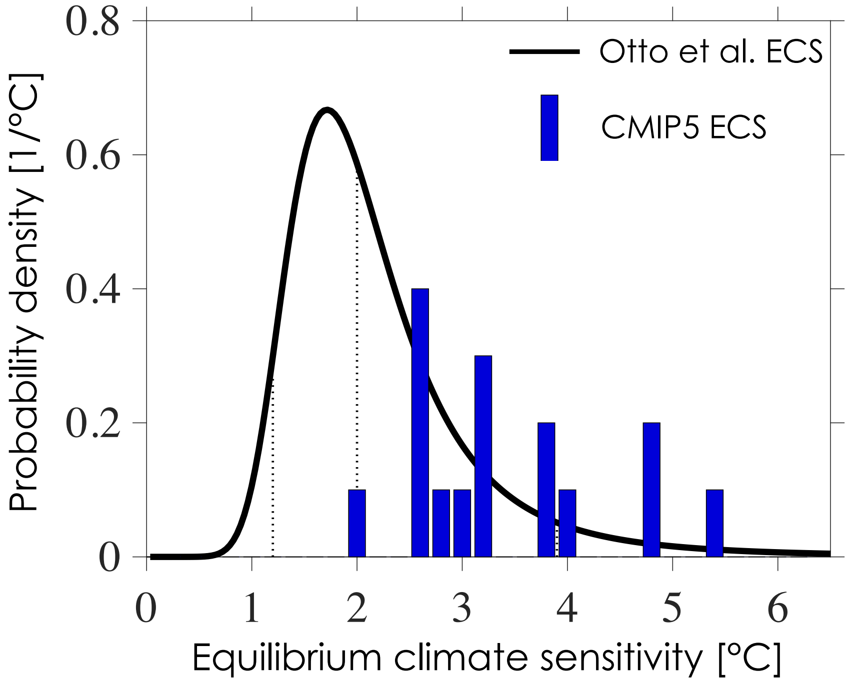
(Armour 2017; see also Proistosescu & Huybers 2017)

Like-with-like comparisons of climate sensitivity

- Emerging consensus: model-observational comparisons must be made in a *like-with-like* way, accounting for possibility that:

    1) Feedbacks (λ) vary over time as the spatial pattern of warming evolves (Armour 2017; Proistosescu & Huybers 2017)

    2) Feedbacks affected by the "efficacy" of non-CO_2 forcings (Shindell 2014; Kummer & Dessler 2014; Marvel et al. 2015)



(Armour 2017; see also Proistosescu & Huybers 2017)

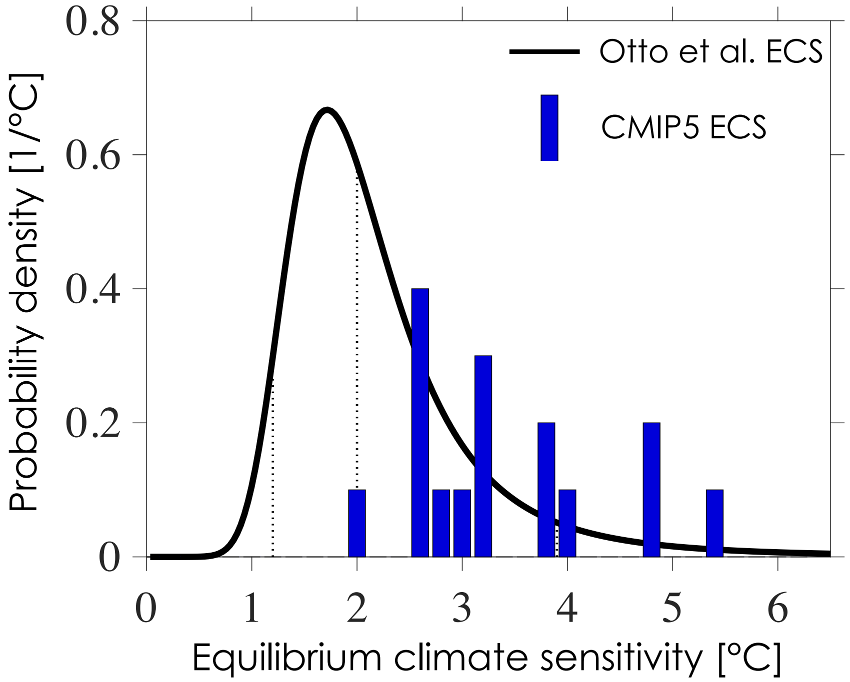
Like-with-like comparisons of climate sensitivity

- Emerging consensus: model-observational comparisons must be made in a *like-with-like* way, accounting for possibility that:

  1) Feedbacks (λ) vary over time as the spatial pattern of warming evolves (Armour 2017; Proistosescu & Huybers 2017)

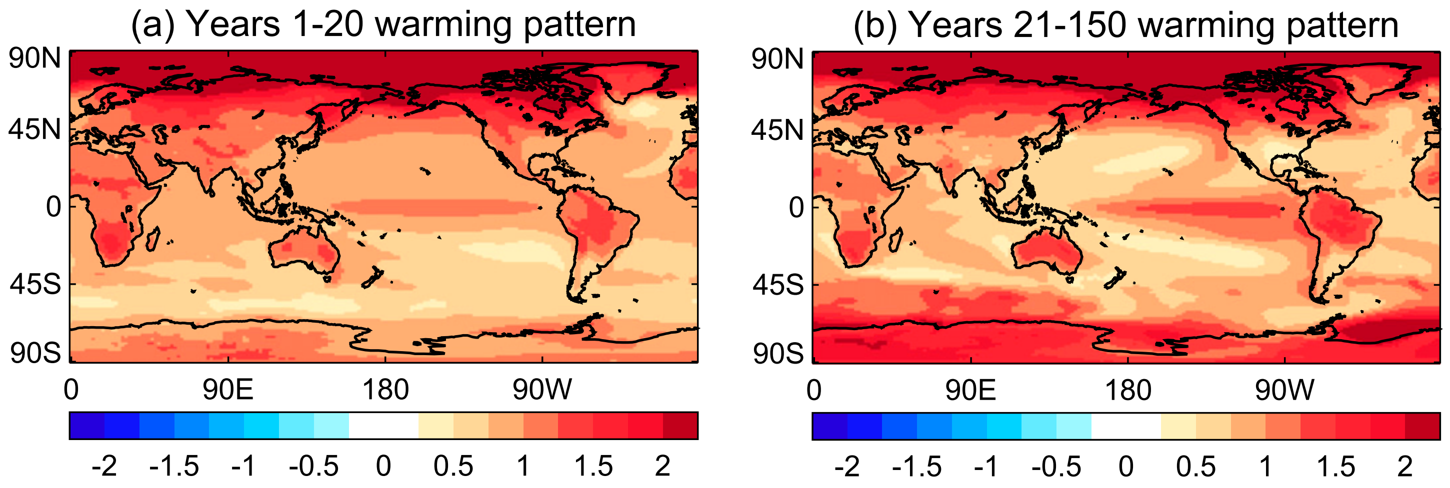
  2) Feedbacks affected by the "efficacy" of non-CO_2 forcings (Shindell 2014; Kummer & Dessler 2014; Marvel et al. 2015)

  3) Feedbacks depend on natural variability in the pattern of warming



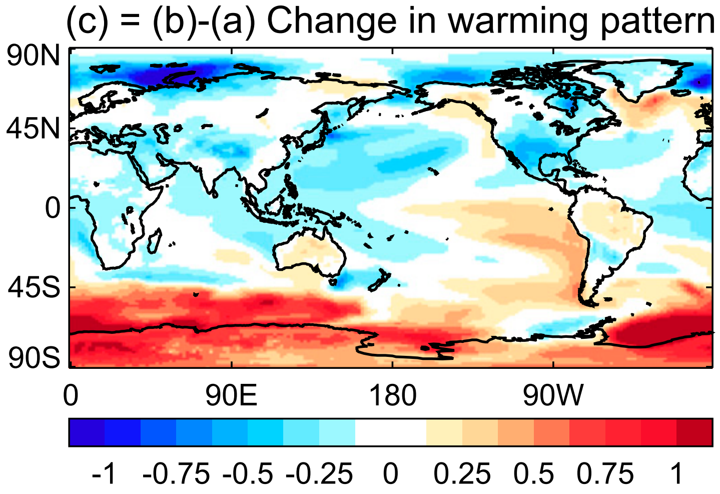
(Armour 2017; see also Proistosescu & Huybers 2017)

1) Feedbacks vary as the pattern of warming evolves



CMIP5 response to $4\times CO_2$ (Andrews et al. 2015)

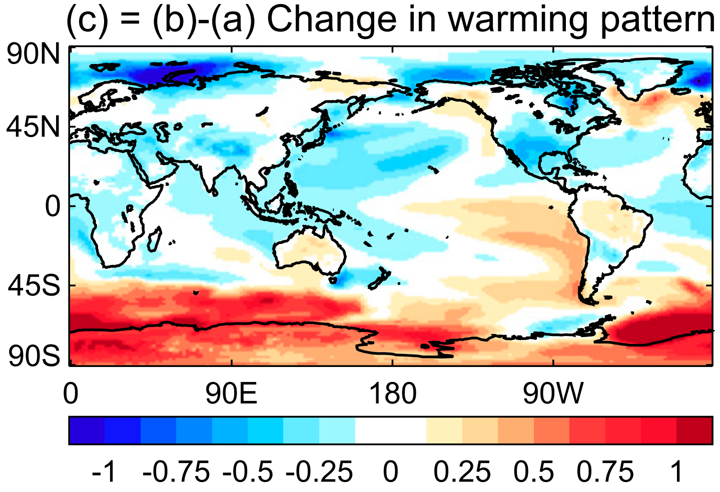
1) Feedbacks vary as the pattern of warming evolves



CMIP5 response to $4\times CO_2$ (Andrews et al. 2015)

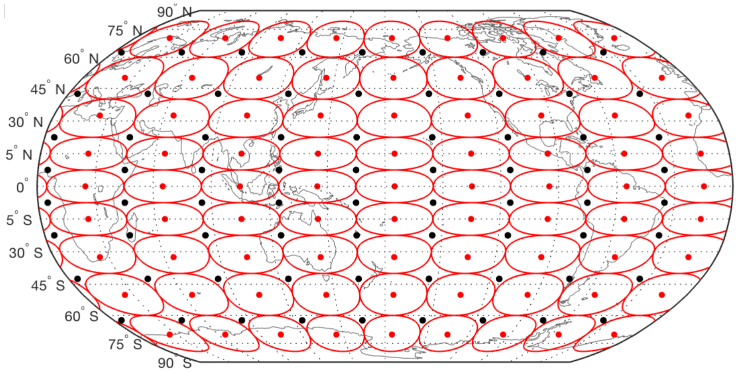
What is the radiative response to this change in warming pattern?

1) Feedbacks vary as the pattern of warming evolves



CMIP5 response to 4×CO_2 (Andrews et al. 2015)

Localized patches of warming

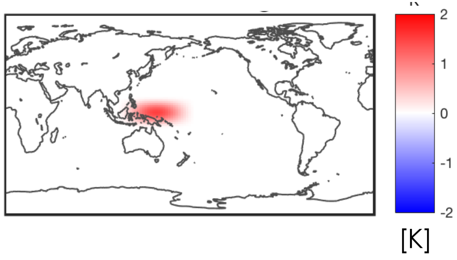


Radiative response to localized patches of warming in NCAR's CAM4 (Dong et al., in preparation)

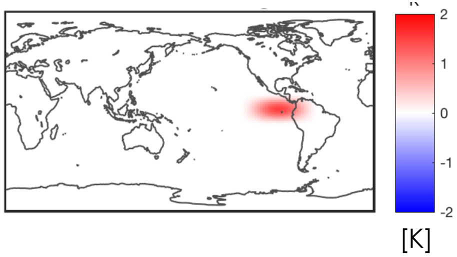
see also Andrews and Webb 2017; Zhou et al. 2016; Zhou et al. 2017

1) Feedbacks vary as the pattern of warming evolves

SST increase in W Pacific



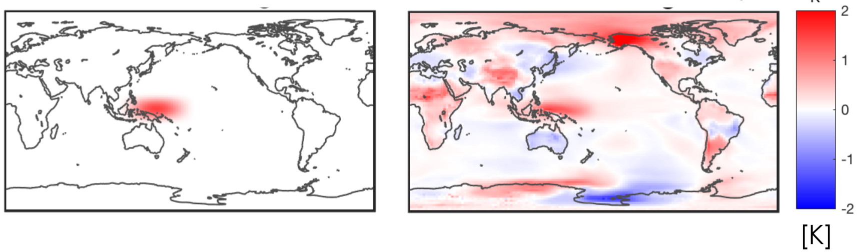
SST increase in E Pacific



1) Feedbacks vary as the pattern of warming evolves

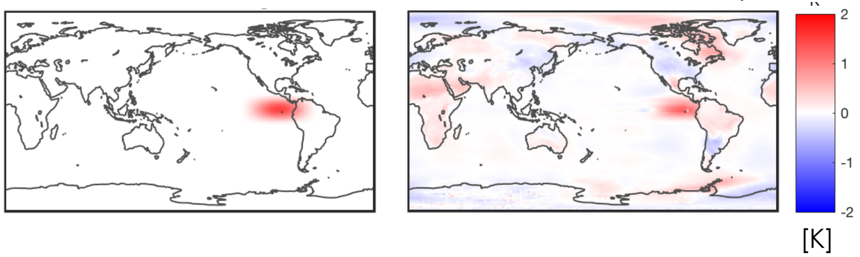
SST increase in W Pacific

Near-surface air temp

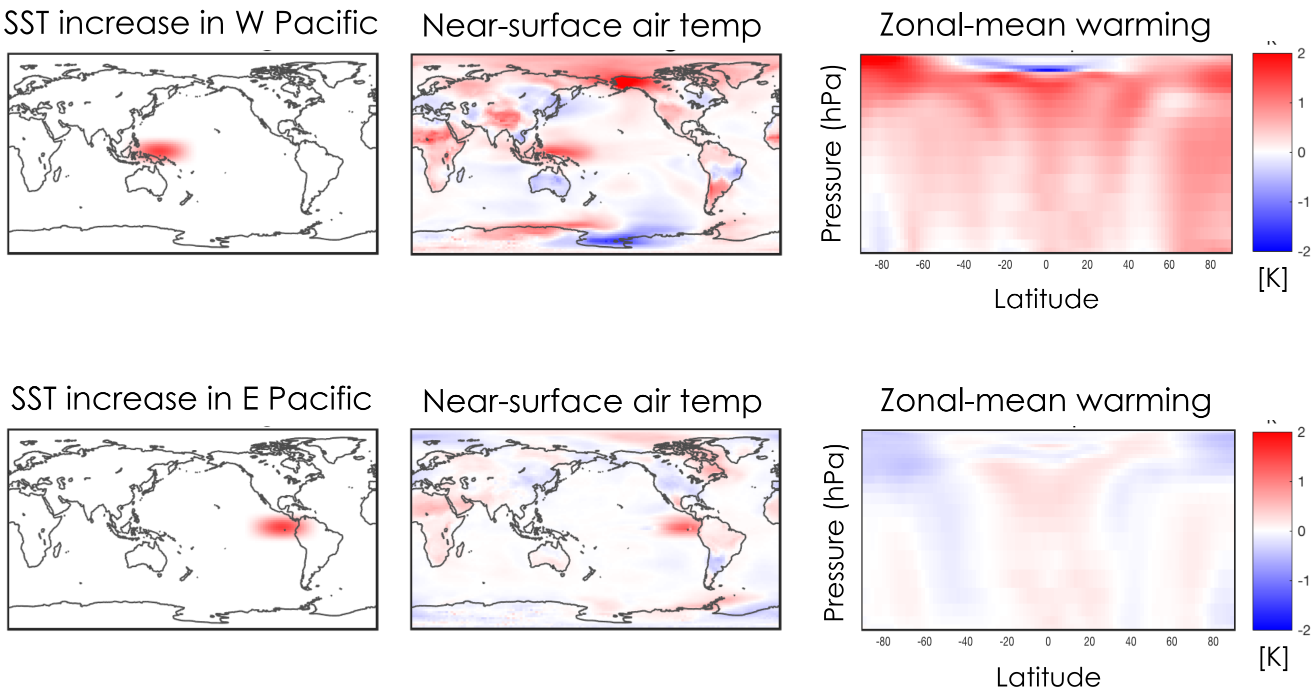


SST increase in E Pacific

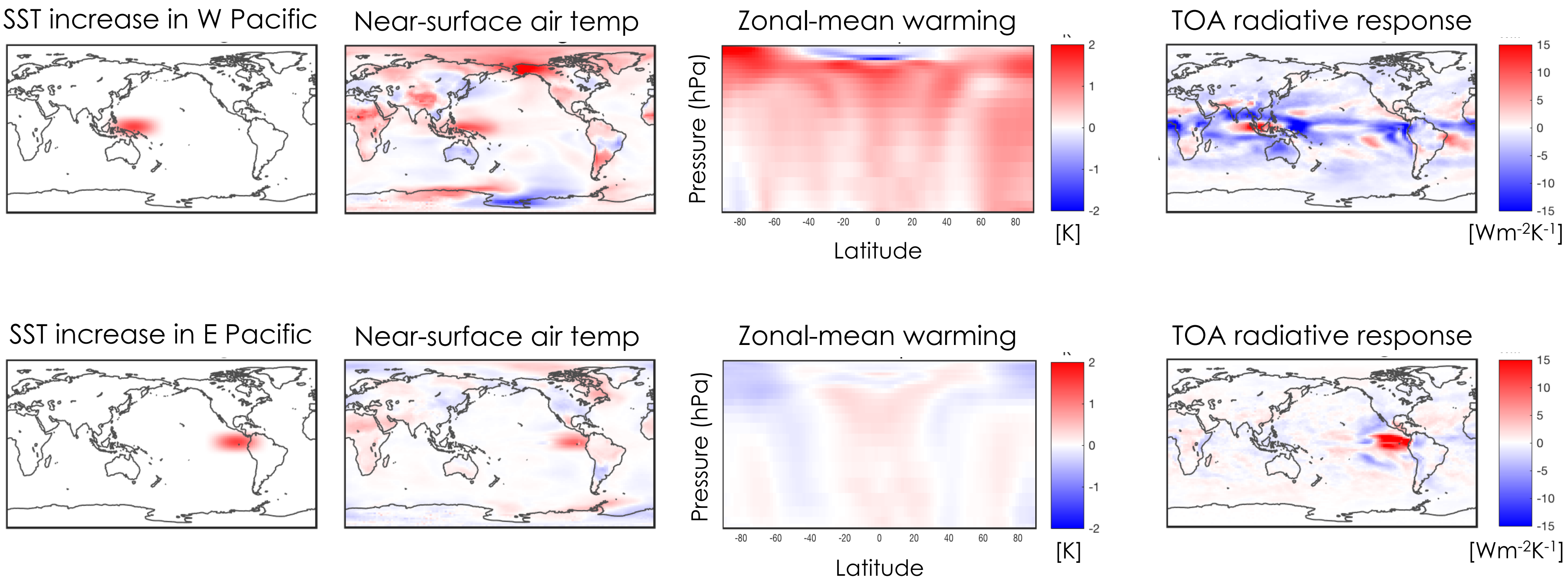
Near-surface air temp



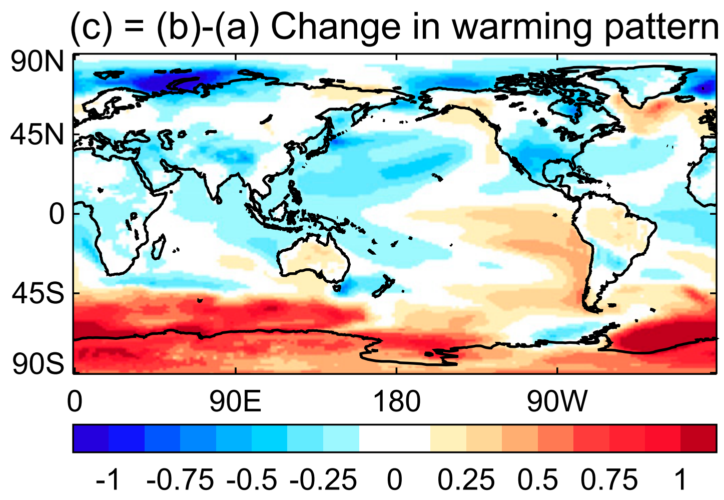
1) Feedbacks vary as the pattern of warming evolves



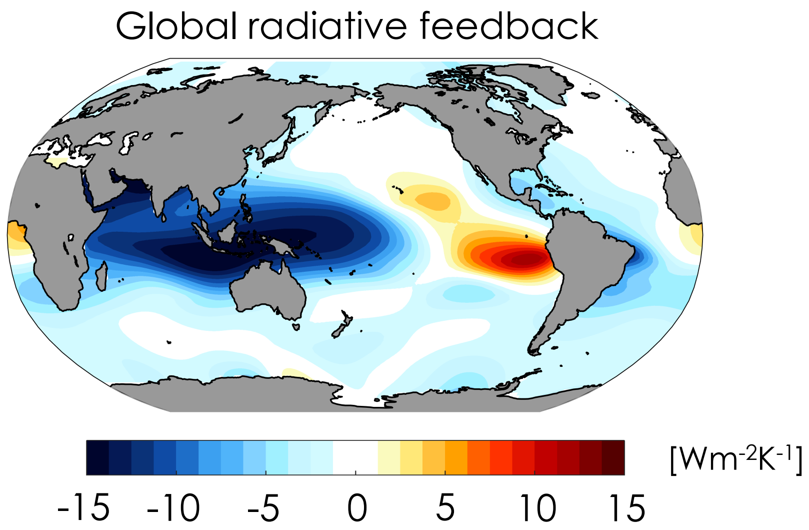
1) Feedbacks vary as the pattern of warming evolves



1) Feedbacks vary as the pattern of warming evolves



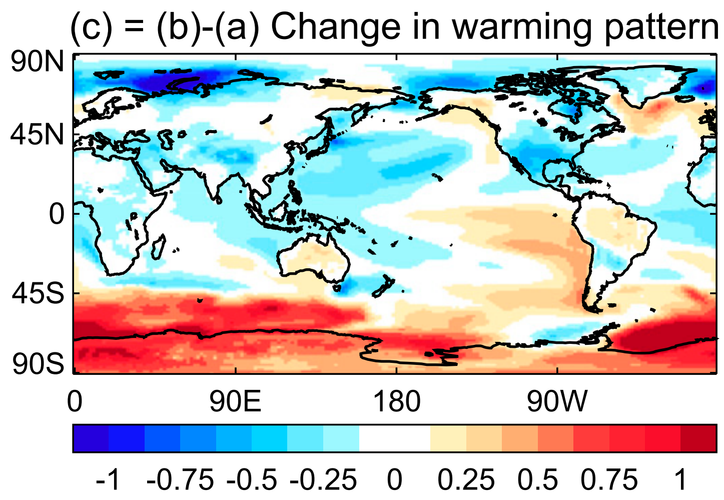
CMIP5 response to $4\times CO_2$ (Andrews et al. 2015)

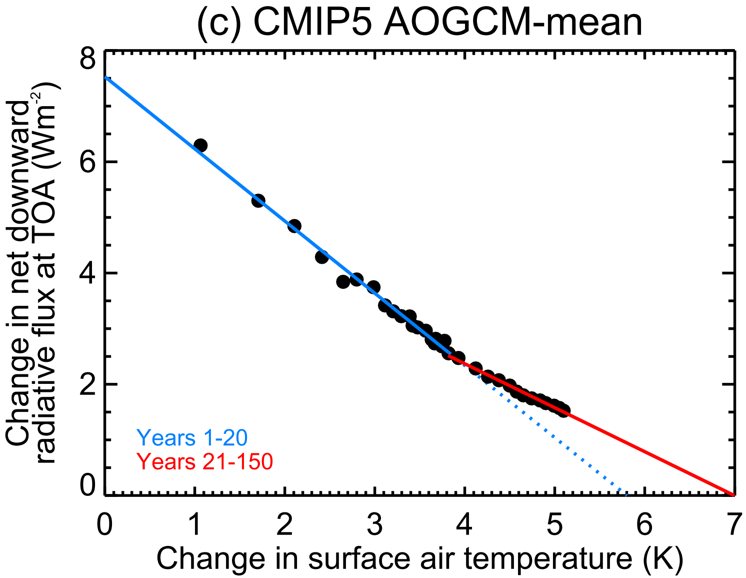


Global feedback response to localized patches of warming in NCAR's CAM4 (Dong et al., in preparation)

see also Andrews and Webb 2017; Zhou et al. 2016; Zhou et al. 2017

1) Feedbacks vary as the pattern of warming evolves



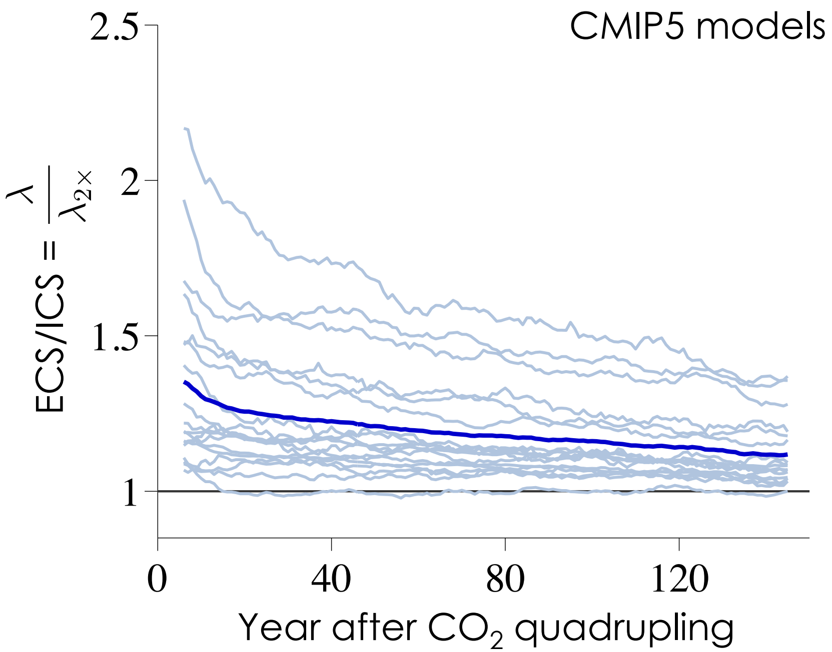


CMIP5 response to $4{\times}CO_2$ (Andrews et al. 2015)

1) Feedbacks vary as the pattern of warming evolves

- Feedbacks under transient warming (λ) are more negative than those at equilibrium ($\lambda_{2\times}$)
- *Inferred* (or *instantaneous*) climate sensitivity (ICS) is generally smaller than *equilibrium* climate sensitivity (ECS)

$$\mathrm{ICS} = -\frac{F_{2\times}}{\lambda} \qquad \mathrm{ECS} = -\frac{F_{2\times}}{\lambda_{2\times}}$$



CMIP5 response to CO_2 forcing (Armour 2017)

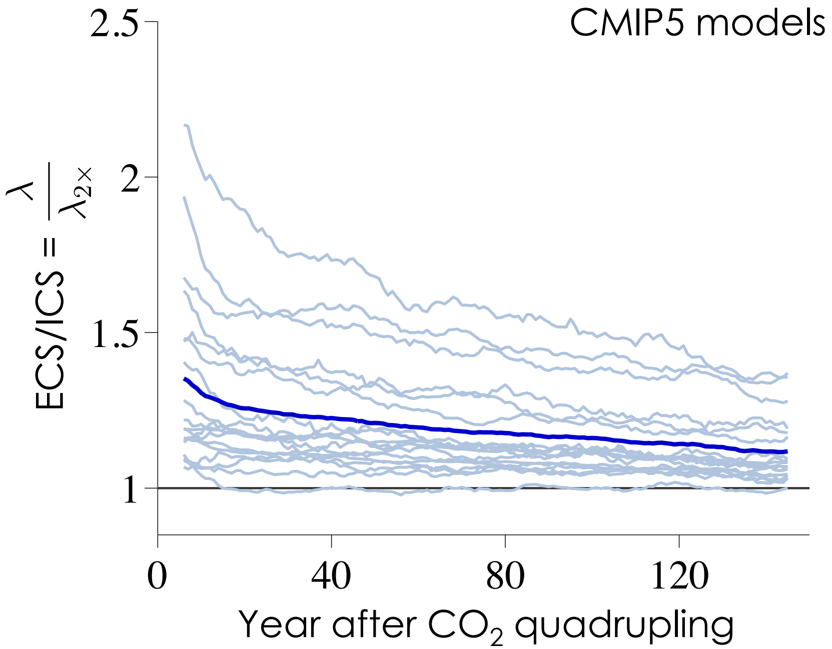
see also Proistosescu & Huybers 2017

1) Feedbacks vary as the pattern of warming evolves

- Feedbacks under transient warming (λ) are more negative than those at equilibrium ($\lambda_{2\times}$)
- *Inferred* (or *instantaneous*) climate sensitivity (ICS) is generally smaller than *equilibrium* climate sensitivity (ECS)

$$\mathrm{ICS} = -\frac{F_{2\times}}{\lambda} = \frac{F_{2\times} T_{\mathrm{obs}}}{F_{\mathrm{obs}} - Q_{\mathrm{obs}}} \qquad \mathrm{ECS} = -\frac{F_{2\times}}{\lambda_{2\times}}$$

- Global energy budget constraints provide estimates of ICS only, so should be compared with model values of ICS (not ECS!)



CMIP5 response to CO_2 forcing (Armour 2017)

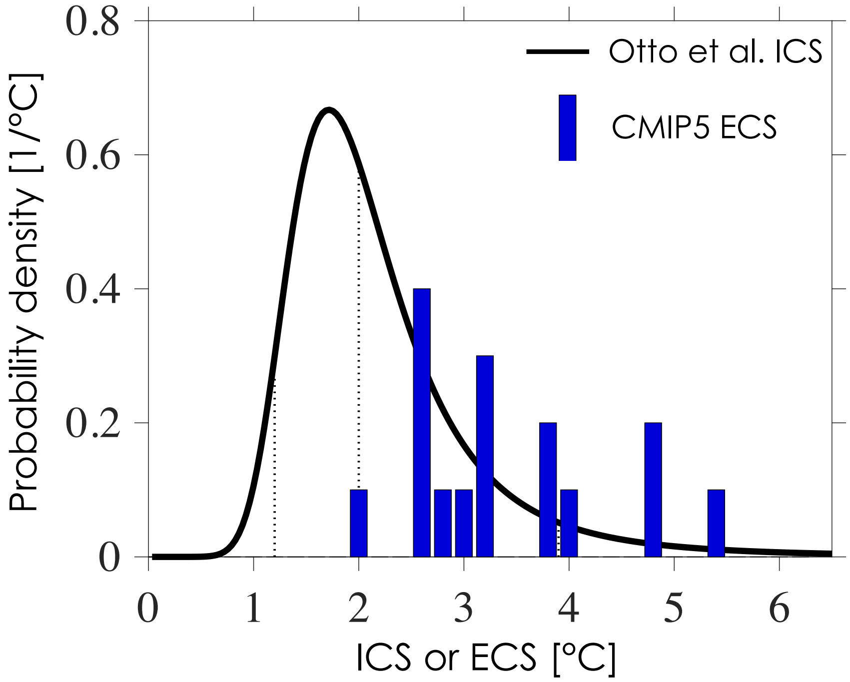
see also Proistosescu & Huybers 2017

1) Feedbacks vary as the pattern of warming evolves

- Feedbacks under transient warming (λ) are more negative than those at equilibrium ($\lambda_{2\times}$)
- *Inferred* (or *instantaneous*) climate sensitivity (ICS) is generally smaller than *equilibrium* climate sensitivity (ECS)

$$\mathrm{ICS} = -\frac{F_{2\times}}{\lambda} = \frac{F_{2\times} T_{\mathrm{obs}}}{F_{\mathrm{obs}} - Q_{\mathrm{obs}}} \qquad \mathrm{ECS} = -\frac{F_{2\times}}{\lambda_{2\times}}$$

- Global energy budget constraints provide estimates of ICS only, so should be compared with model values of ICS (not ECS!)



CMIP5 response to CO_2 forcing (Armour 2017)

see also Proistosescu & Huybers 2017

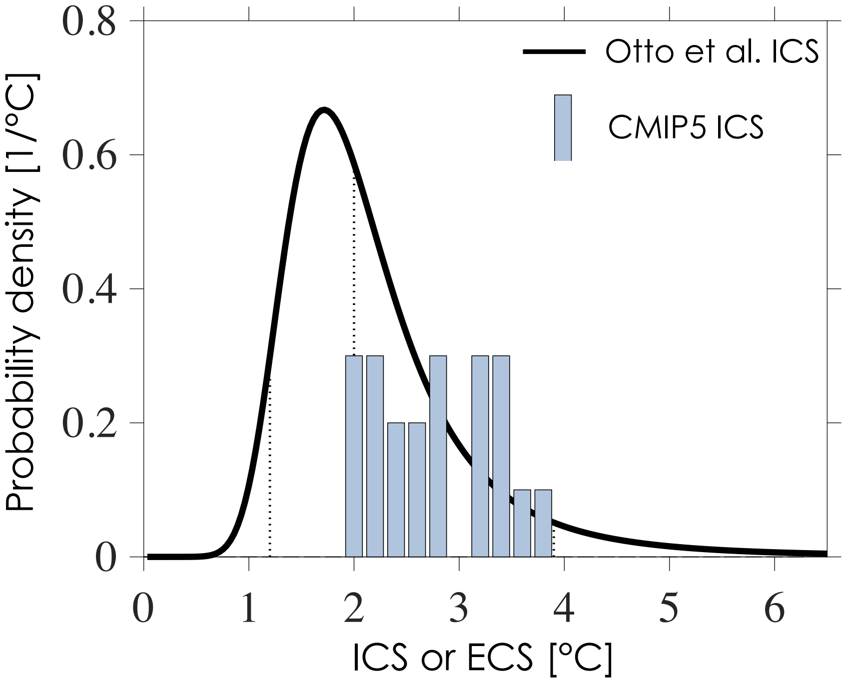
1) Feedbacks vary as the pattern of warming evolves

- Feedbacks under transient warming (λ) are more negative than those at equilibrium ($\lambda_{2\times}$)
- *Inferred* (or *instantaneous*) climate sensitivity (ICS) is generally smaller than *equilibrium* climate sensitivity (ECS)

$$\mathrm{ICS} = -\frac{F_{2\times}}{\lambda} = \frac{F_{2\times} T_{\mathrm{obs}}}{F_{\mathrm{obs}} - Q_{\mathrm{obs}}}$$

$$\mathrm{ECS} = -\frac{F_{2\times}}{\lambda_{2\times}}$$

- Global energy budget constraints provide estimates of ICS only, so should be compared with model values of ICS (not ECS!)

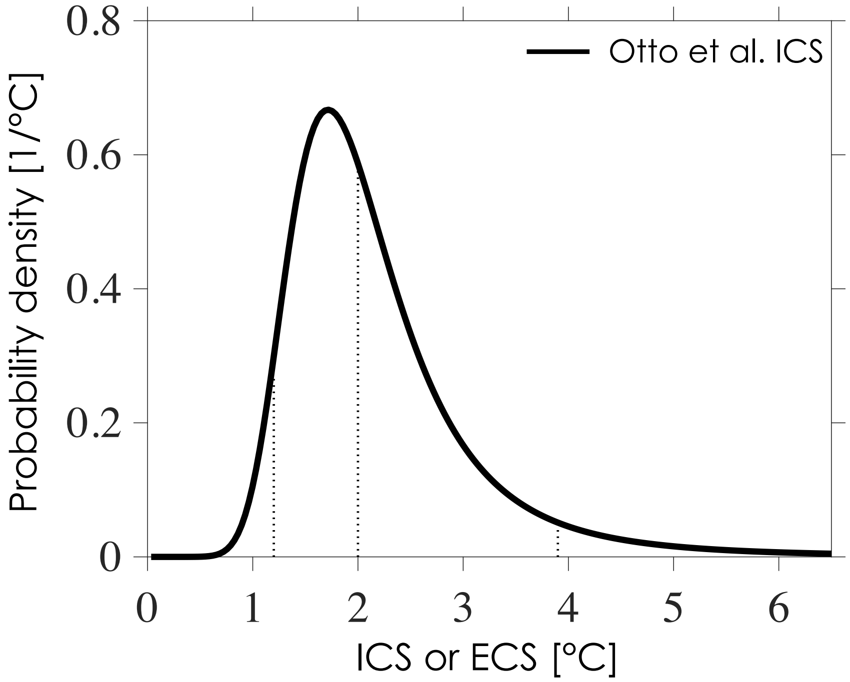


CMIP5 response to CO_2 forcing (Armour 2017)

see also Proistosescu & Huybers 2017

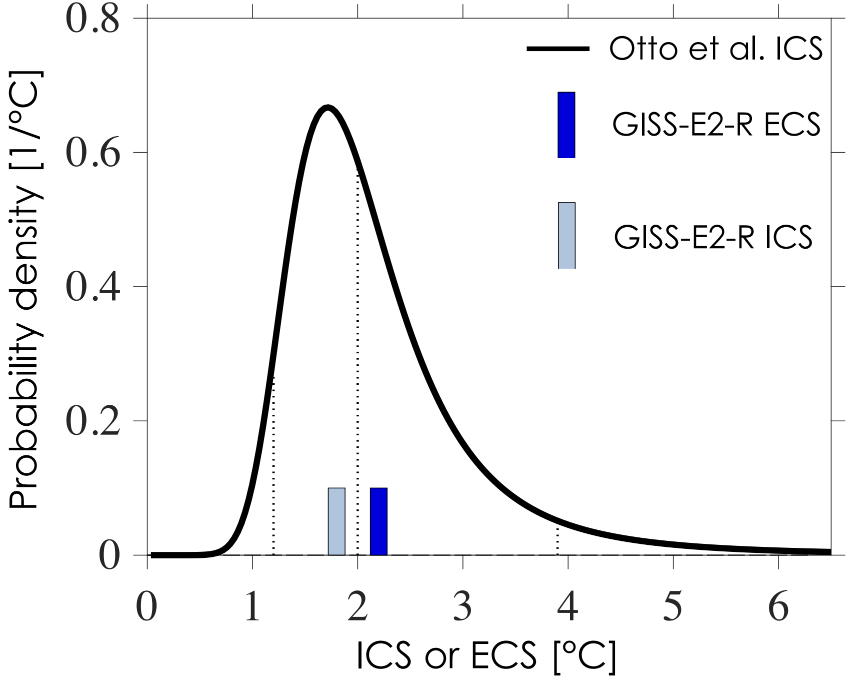
2) Feedbacks depend on the type of radiative forcing

- Feedbacks under historical forcing may differ from those under CO_2 forcing alone (Shindell 2014; Marvel et al. 2015)
- Radiative Forcing Model Intercomparison Project (RFMIP; Pincus et al. 2016) protocol produces coupled model estimates of forcing and feedbacks over historical period



2) Feedbacks depend on the type of radiative forcing

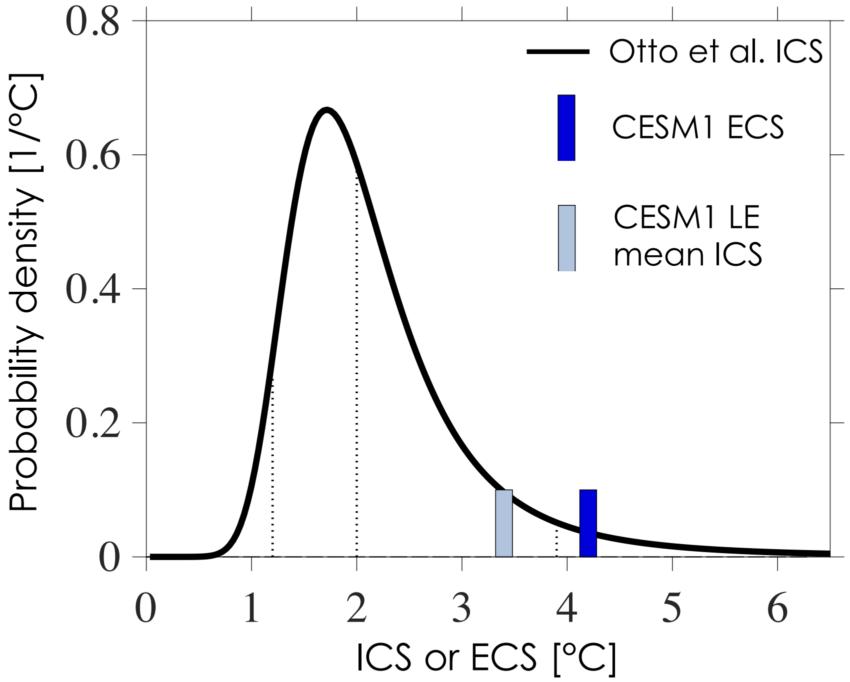
- Feedbacks under historical forcing may differ from those under CO_2 forcing alone (Shindell 2014; Marvel et al. 2015)
- Radiative Forcing Model Intercomparison Project (RFMIP; Pincus et al. 2016) protocol produces coupled model estimates of forcing and feedbacks over historical period



Historical simulations with GISS-E2-R
(Marvel et al. 2015)

2) Feedbacks depend on the type of radiative forcing

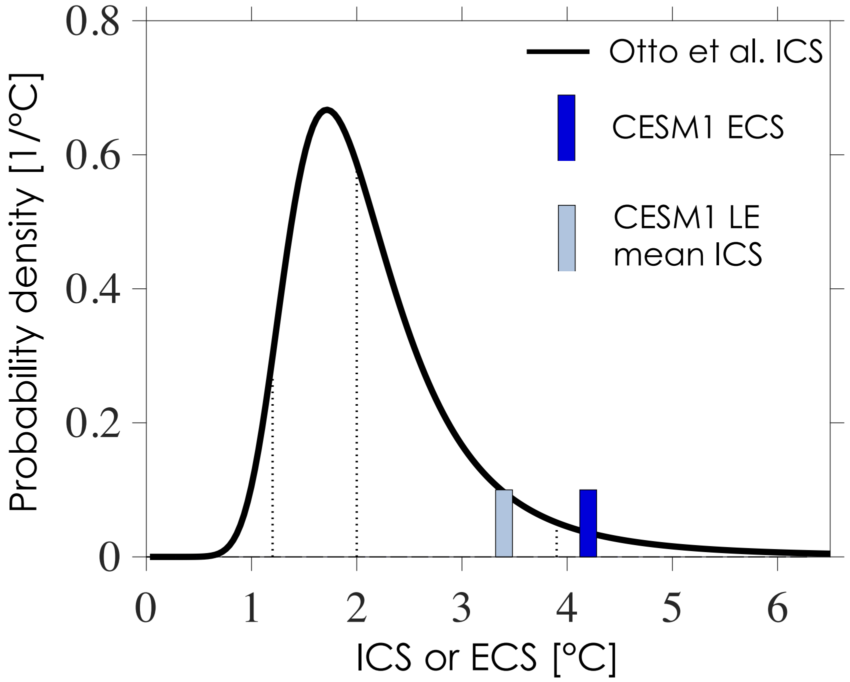
- Feedbacks under historical forcing may differ from those under CO_2 forcing alone (Shindell 2014; Marvel et al. 2015)
- Radiative Forcing Model Intercomparison Project (RFMIP; Pincus et al. 2016) protocol produces coupled model estimates of forcing and feedbacks over historical period



Historical simulations of NCAR's CESM1-CAM5 Large Ensemble

3) Feedbacks vary due to internal climate variability

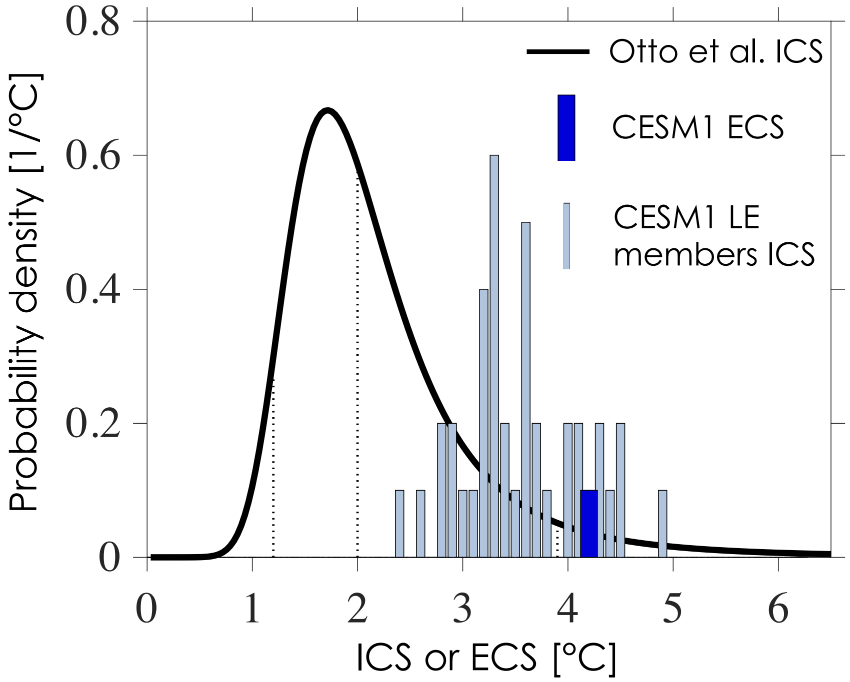
- Feedbacks under historical forcing can vary due to only internal climate variability (Dessler et al. 2018)



Historical simulations of NCAR's CESM1-CAM5 Large Ensemble

3) Feedbacks vary due to internal climate variability

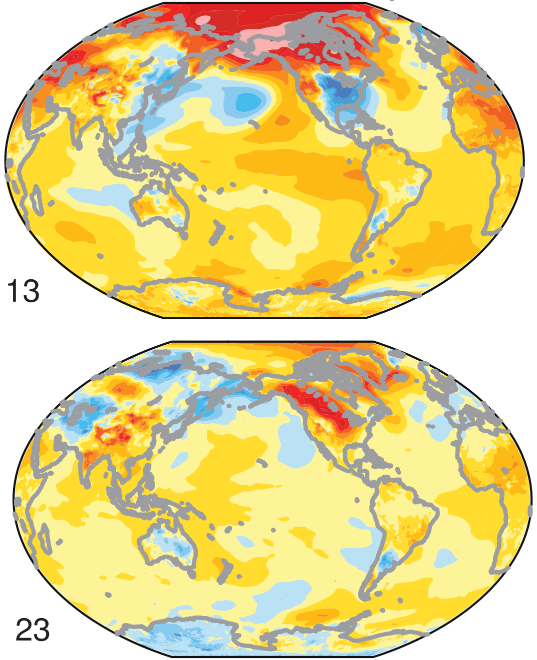
- Feedbacks under historical forcing can vary due to only internal climate variability (Dessler et al. 2018)



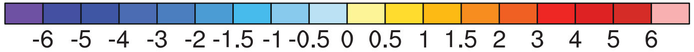
Historical simulations of NCAR's CESM1-CAM5 Large Ensemble

3) Feedbacks vary due to internal climate variability

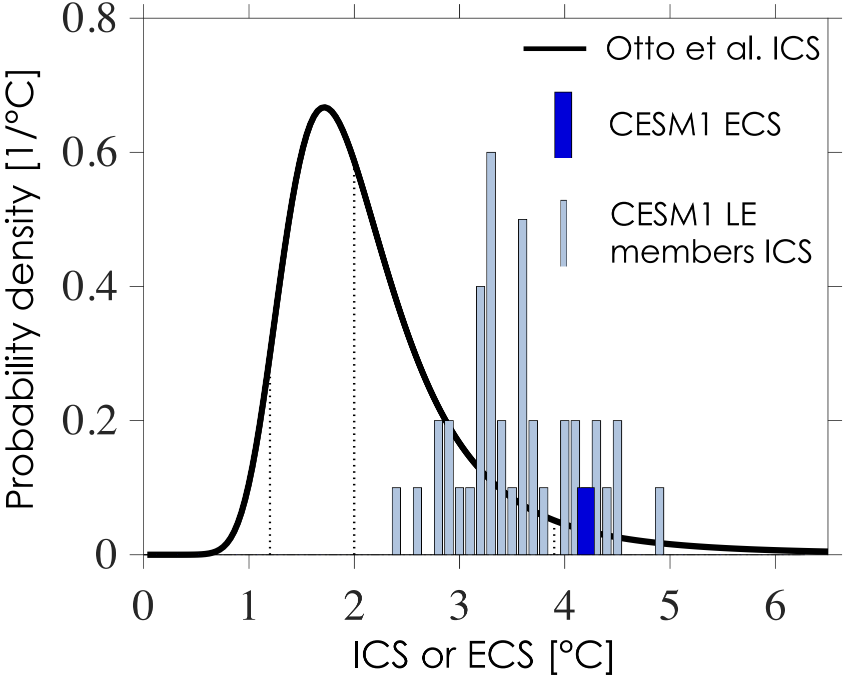
- Feedbacks under historical forcing can vary due to only internal climate variability (Dessler et al. 2018)



1979-2012 DJF surface air temperature trends (K/34 years)



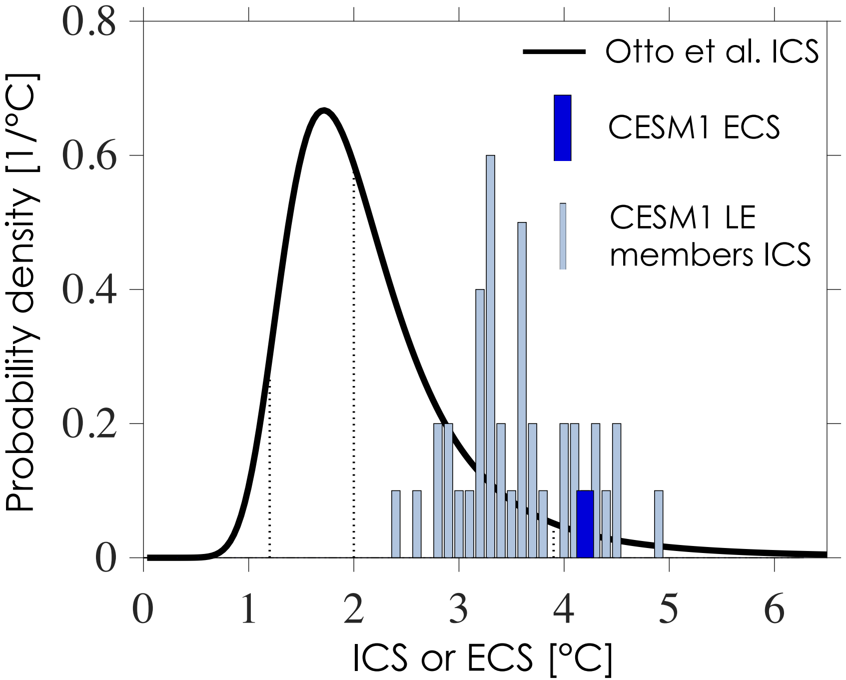
Kay et al (2015)



Historical simulations of NCAR's CESM1-CAM5 Large Ensemble

3) Feedbacks vary due to internal climate variability

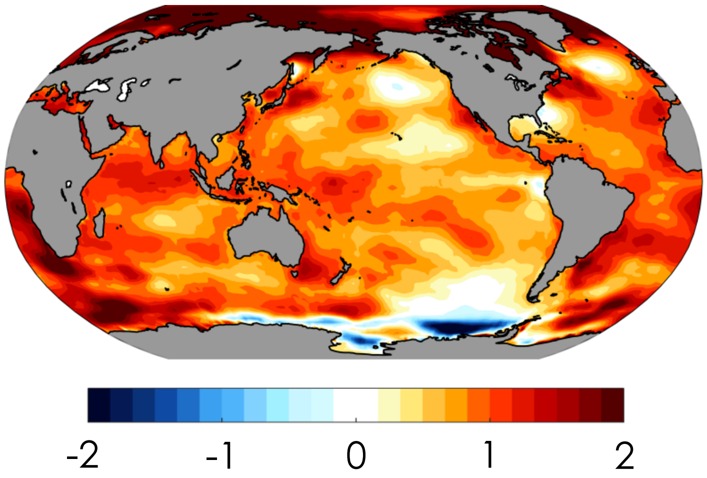
- Feedbacks under historical forcing can vary due to only internal climate variability (Dessler et al. 2018)
- Key question: what global feedback (and ICS) has the observed warming pattern engendered?
    - absent this knowledge, this internal variability uncertainty is swamped by the forcing uncertainty
    - can be thought of as uncertainty that would remain given perfect observations of forcing, heat uptake, etc



Historical simulations of NCAR's CESM1-CAM5 Large Ensemble

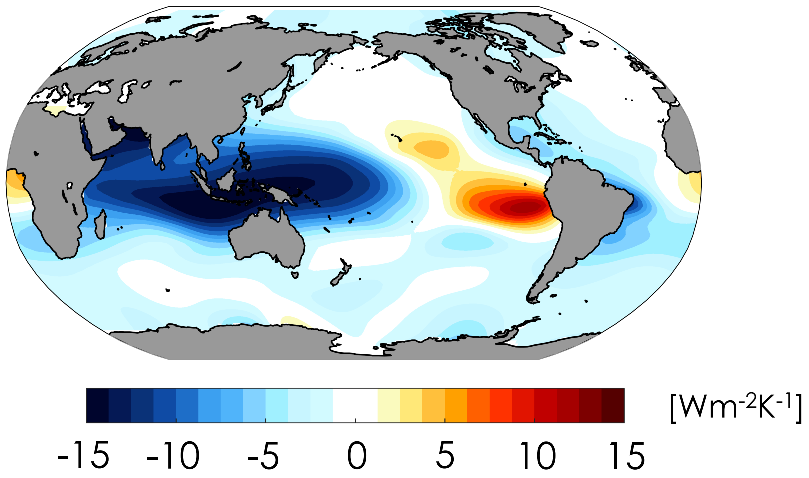
3) Feedbacks vary due to internal climate variability

Observed warming pattern



AMIP II boundary conditions (Hurrell et al. 2008)

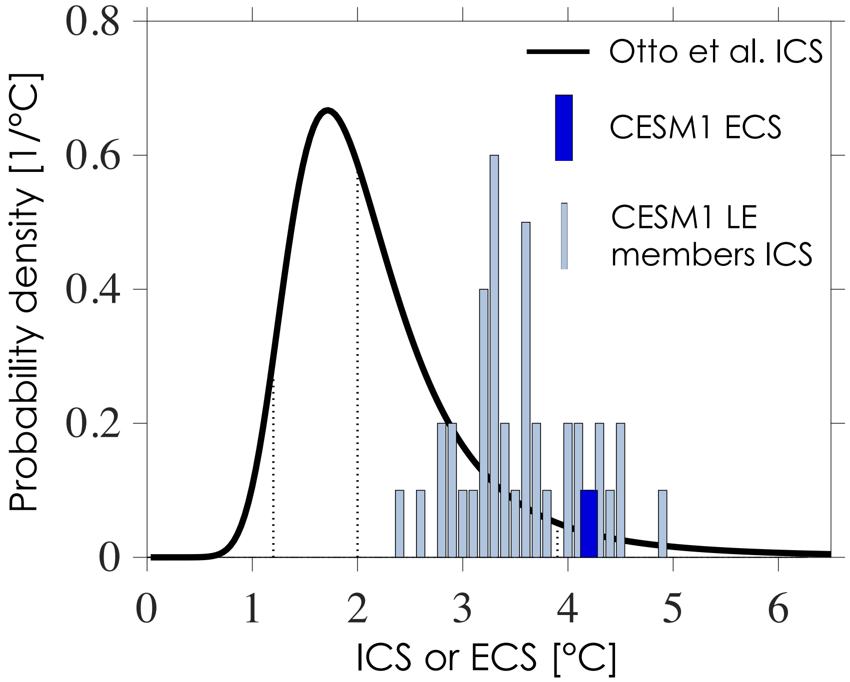
Global radiative feedback



Global feedback response to localized patches of warming in NCAR's CAM4 (Dong et al., in preparation)

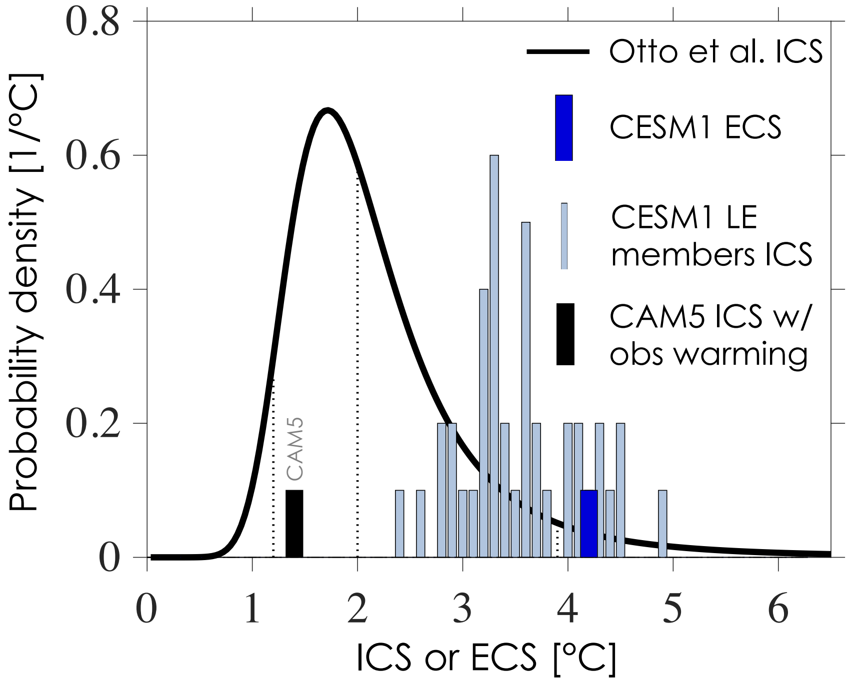
3) Feedbacks vary due to internal climate variability

- Prescribed sea-surface temperature (SST) simulations produce the same feedbacks as are induced by climate forcings (Haugstad et al. 2017)
- Cloud Feedback Model Intercomparison Project (CFMIP; Webb et al. 2017) protocol produces estimates of feedbacks associated with observed warming pattern



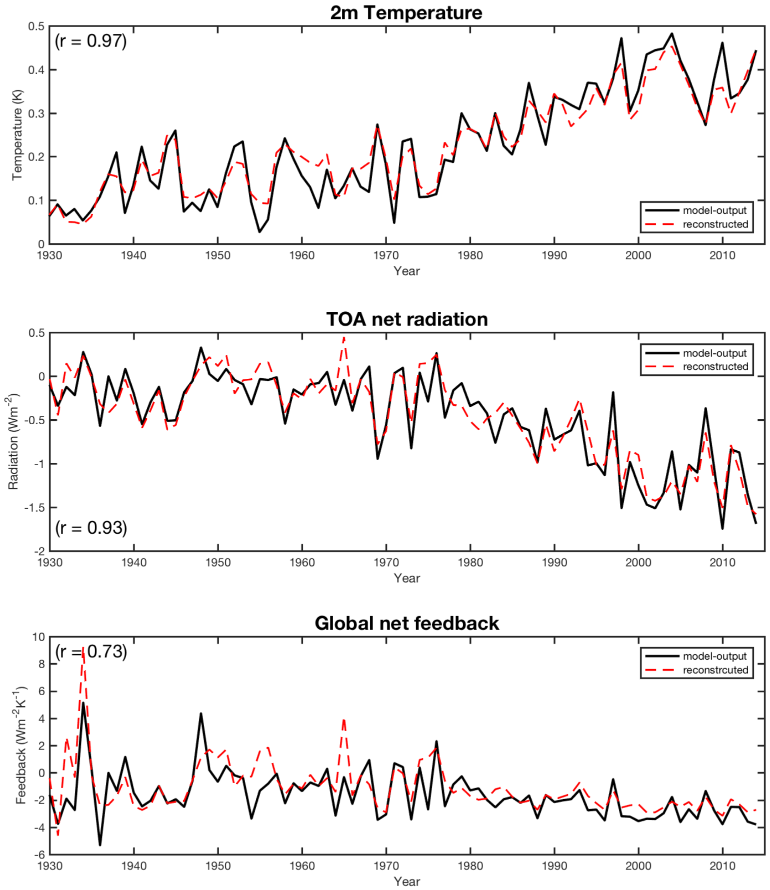
3) Feedbacks vary due to internal climate variability

- Prescribed sea-surface temperature (SST) simulations produce the same feedbacks as are induced by climate forcings (Haugstad et al. 2017)
- Cloud Feedback Model Intercomparison Project (CFMIP; Webb et al. 2017) protocol produces estimates of feedbacks associated with observed warming pattern



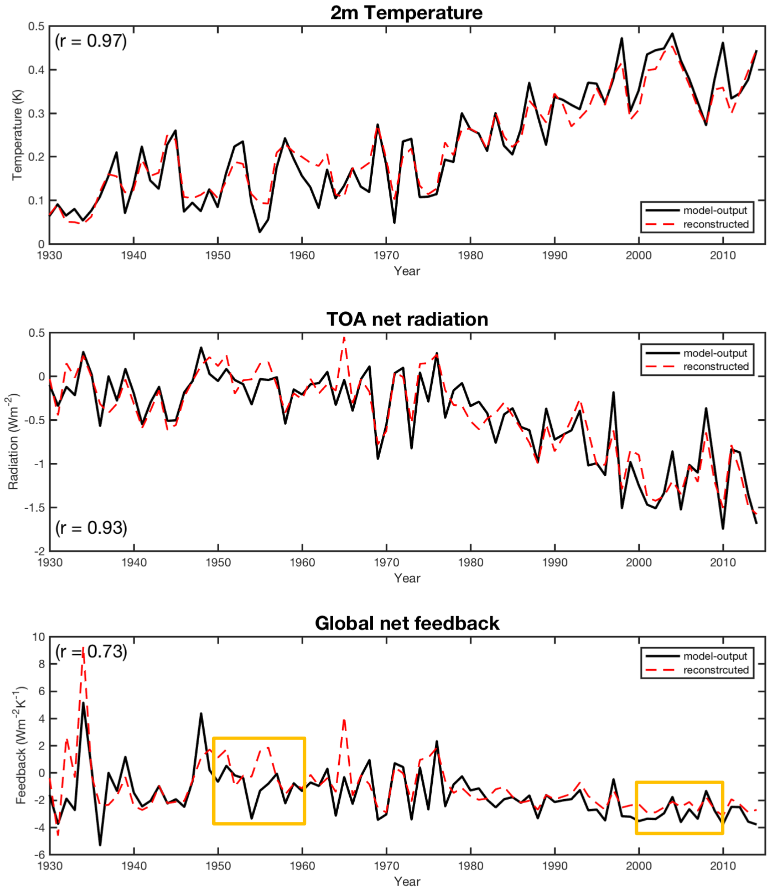
Prescribed observed SST simulation with CAM5

3) Feedbacks vary due to internal climate variability



Global near-surface air temperature, TOA radiation and global radiative feedback well-reconstructed by Green's function

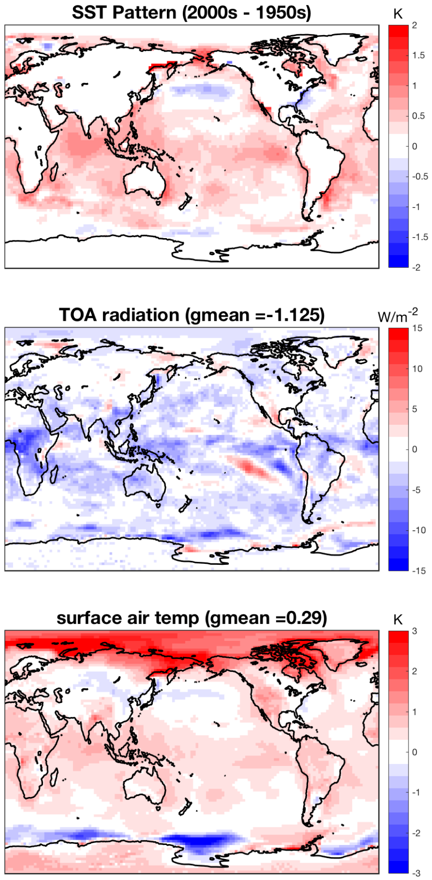
3) Feedbacks vary due to internal climate variability



Global near-surface air temperature, TOA radiation and global radiative feedback well-reconstructed by Green's function

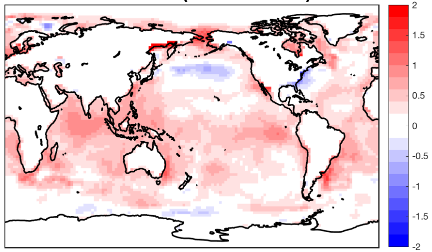
What regions contribute most to the increasingly negative radiative feedback in recent decades?

3) Feedbacks vary due to internal climate variability

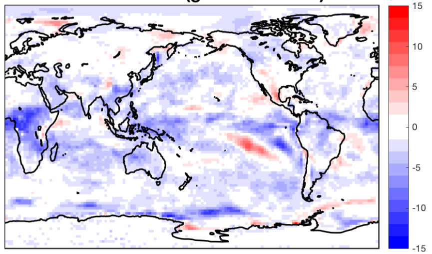


3) Feedbacks vary due to internal climate variability

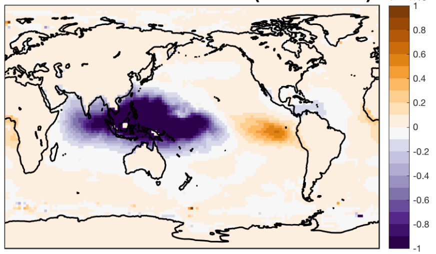
SST Pattern (2000s - 1950s)



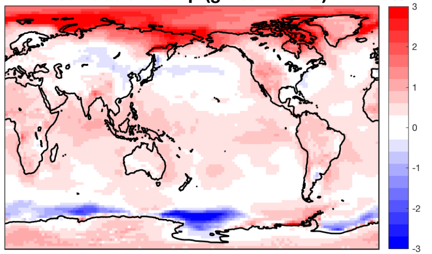
TOA radiation (gmean =-1.125)



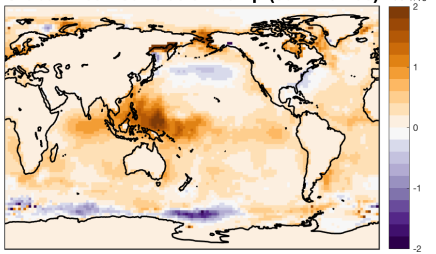
Global mean TOA radiation (sum =-0.793)



surface air temp (gmean =0.29)



Global mean surface air temp (sum =0.259)

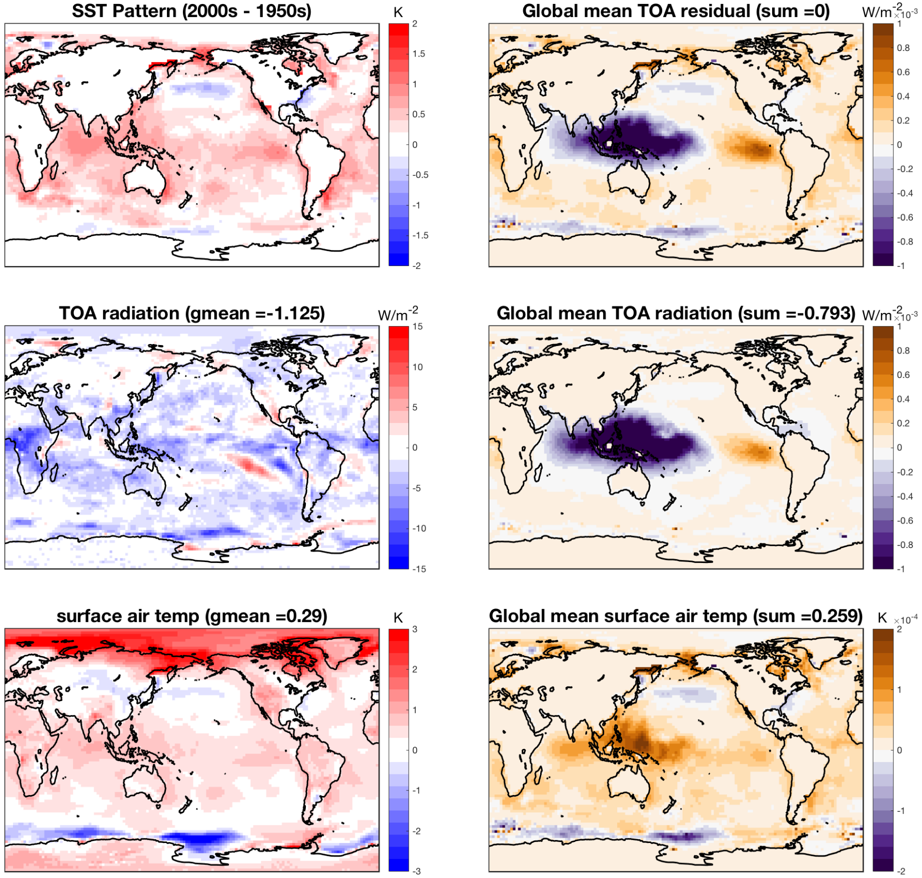


Green's functions tell you which regions contributed most to global TOA radiation (Q) or surface warming (T_s)

$$\left.\frac{\partial \overline{Q}}{\partial \mathrm{SST}}\right|_i \Delta \mathrm{SST}_i$$

$$\left.\frac{\partial \overline{T_s}}{\partial \mathrm{SST}}\right|_i \Delta \mathrm{SST}_i$$

3) Feedbacks vary due to internal climate variability



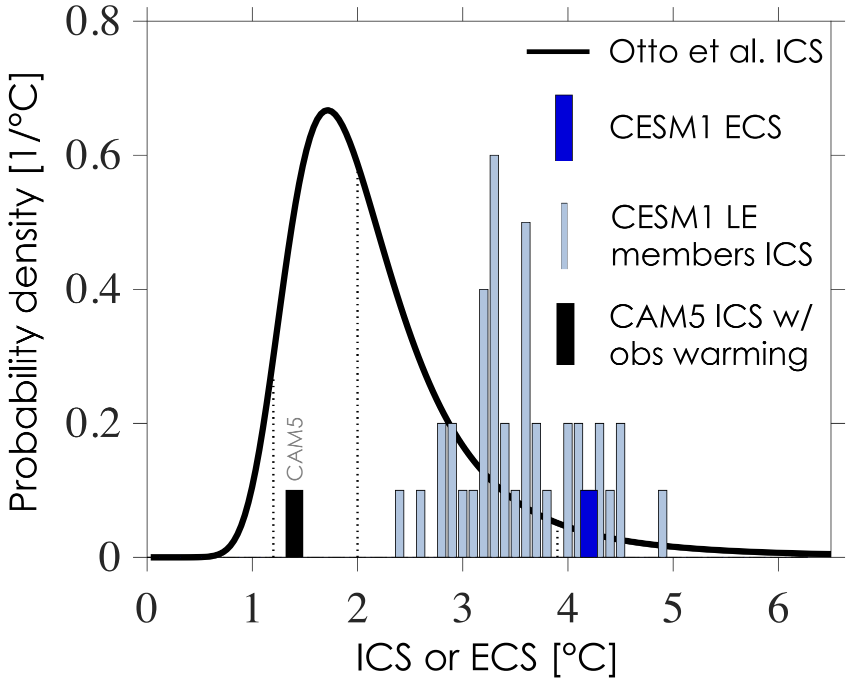
$$\frac{\partial \overline{Q}}{\partial \mathrm{SST}}\bigg|_i \Delta \mathrm{SST}_i - \lambda_{\mathrm{global}} \frac{\partial \overline{T_s}}{\partial \mathrm{SST}}\bigg|_i \Delta \mathrm{SST}_i$$

This quantity equals zero in the global mean (by definition) but tells you what regions most contribute to global feedback changes due to regional radiative response to warming being different from the global feedback

West Pacific warming (negative feedback) wins out over all other regions (generally positive feedbacks), small contribution from Southern Ocean cooling

3) Feedbacks vary due to internal climate variability

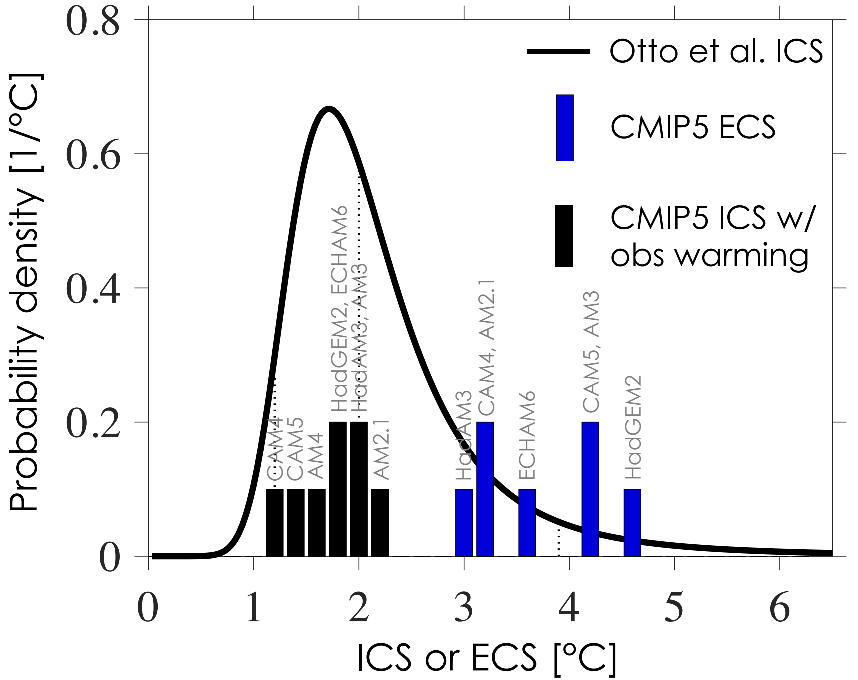
- Prescribed sea-surface temperature (SST) simulations produce the same feedbacks as are induced by climate forcings (Haugstad et al. 2017)
- Cloud Feedback Model Intercomparison Project (CFMIP; Webb et al. 2017) protocol produces estimates of feedbacks associated with observed warming pattern



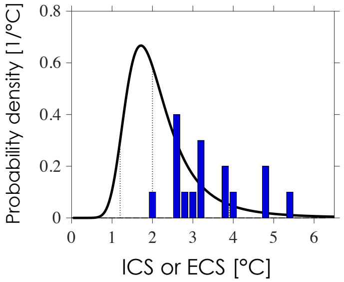
Prescribed observed SST simulation with CAM5

3) Feedbacks vary due to internal climate variability

- Prescribed sea-surface temperature (SST) simulations produce the same feedbacks as are induced by climate forcings (Haugstad et al. 2017)
- Cloud Feedback Model Intercomparison Project (CFMIP; Webb et al. 2017) protocol produces estimates of feedbacks associated with observed warming pattern

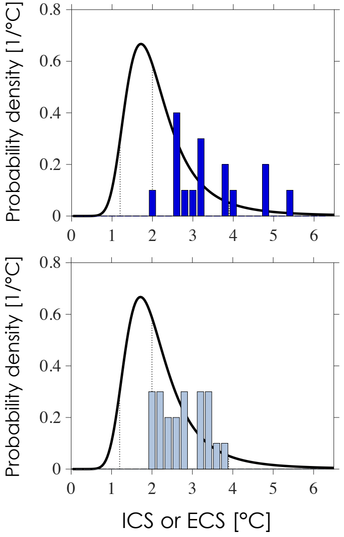


Prescribed observed SST simulations with CAM4, CAM5, HadGEM2, HadAM3, ECHAM6, AM2.1, AM3, AM4 (Yue Dong, Malte Stuecker, Cristi Proistosescu, Tim Andrews, Jonathan Gregory, Thorsten Mauritsen, Levi Silvers & David Paynter)



Parting thoughts

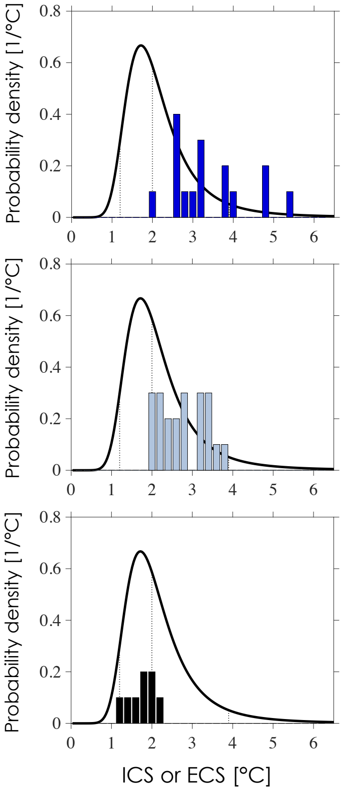
- Apparent offset between global energy budget constraints and models stems from sloppy comparison between observation-based estimates of ICS and modeled estimates of ECS



Parting thoughts

- Apparent offset between global energy budget constraints and models stems from sloppy comparison between observation-based estimates of ICS and modeled estimates of ECS

- Accounting for feedback dependence on evolving pattern of CO_2-forced warming (slow warming of E. Pacific and Southern Ocean) gives model values of ICS that are in agreement with observation-based values (though still high)

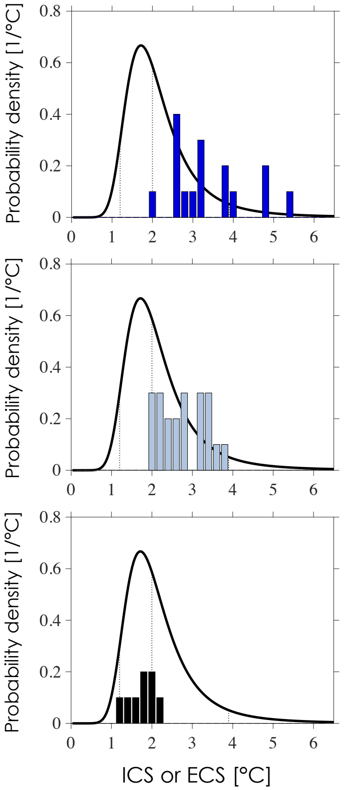


Parting thoughts

- Apparent offset between global energy budget constraints and models stems from sloppy comparison between observation-based estimates of ICS and modeled estimates of ECS

- Accounting for feedback dependence on evolving pattern of CO_2-forced warming (slow warming of E. Pacific and Southern Ocean) gives model values of ICS that are in agreement with observation-based values (though still high)

- Accounting for the observed pattern of warming being pretty odd gives model values of ICS that are in good agreement



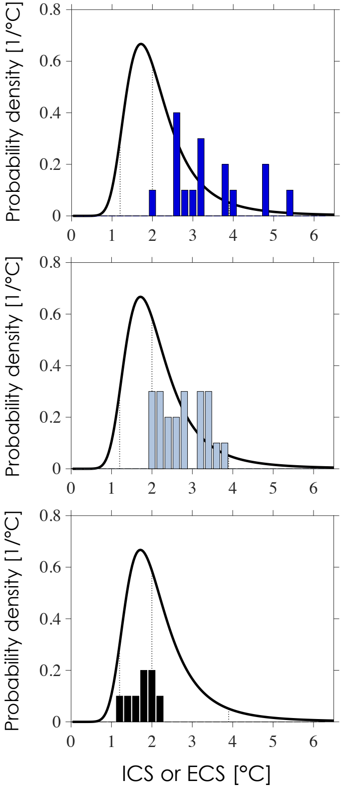
Parting thoughts

- Apparent offset between global energy budget constraints and models stems from sloppy comparison between observation-based estimates of ICS and modeled estimates of ECS

- Accounting for feedback dependence on evolving pattern of CO_2-forced warming (slow warming of E. Pacific and Southern Ocean) gives model values of ICS that are in agreement with observation-based values (though still high)

- Accounting for the observed pattern of warming being pretty odd gives model values of ICS that are in good agreement

- How can ECS be constrained from observations, given that the observational record has coincided with a particularly strange pattern of warming? We are unsure if future warming patterns predicted by models are realistic given that they fail to get the observed warming pattern right



Parting thoughts

- Apparent offset between global energy budget constraints and models stems from sloppy comparison between observation-based estimates of ICS and modeled estimates of ECS

- Accounting for feedback dependence on evolving pattern of CO_2-forced warming (slow warming of E. Pacific and Southern Ocean) gives model values of ICS that are in agreement with observation-based values (though still high)

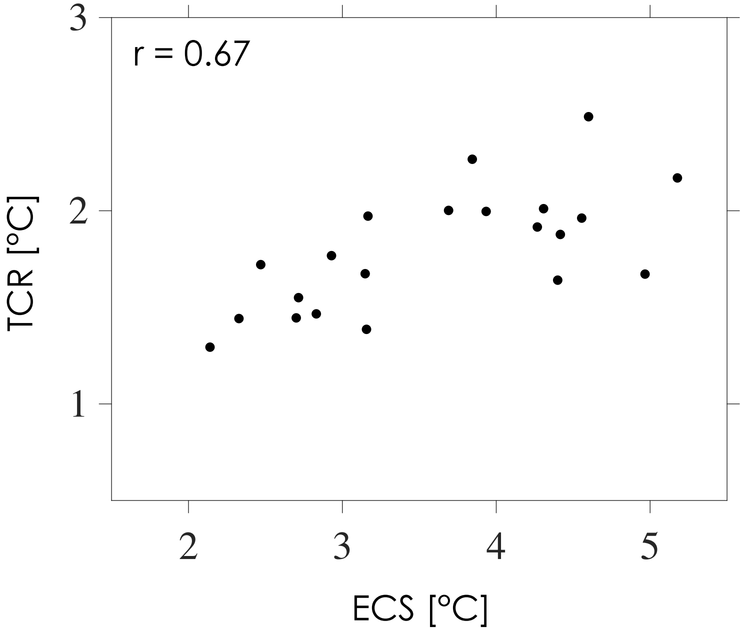
- Accounting for the observed pattern of warming being pretty odd gives model values of ICS that are in good agreement

- How can ECS be constrained from observations, given that the observational record has coincided with a particularly strange pattern of warming? We are unsure if future warming patterns predicted by models are realistic given that they fail to get the observed warming pattern right

- How much of the intermodel spread in ECS might be due cloud response to different SST patterns, rather than different cloud physics/parameterizations?

An aside: does ECS or ICS matter more for transient warming?

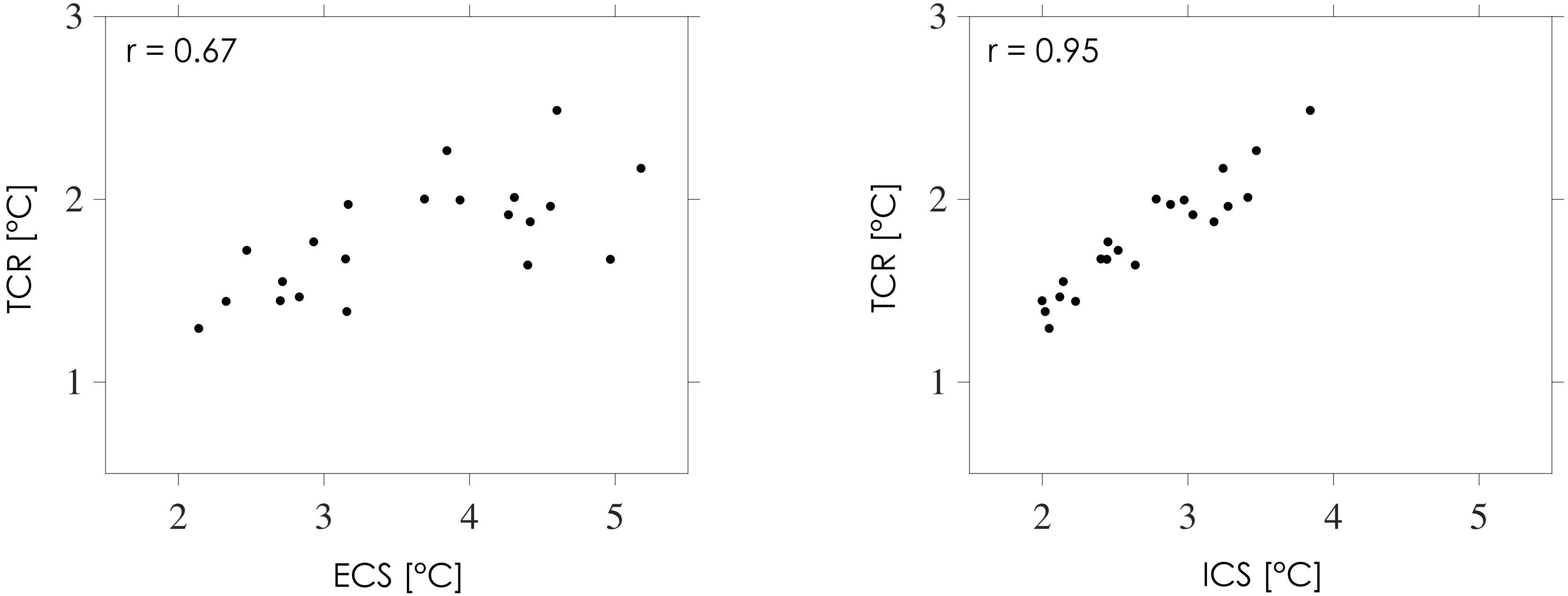
- Transient warming is weekly correlated with ECS



TCR = warming at year 70, the time of CO_2 doubling under 1%/yr CO2 ramping

An aside: does ECS or ICS matter more for transient warming?

- Transient warming is weekly correlated with ECS
- Transient warming is highly correlated with ICS



TCR = warming at year 70, the time of CO_2 doubling under 1%/yr CO2 ramping

Like-with-like comparisons of climate sensitivity

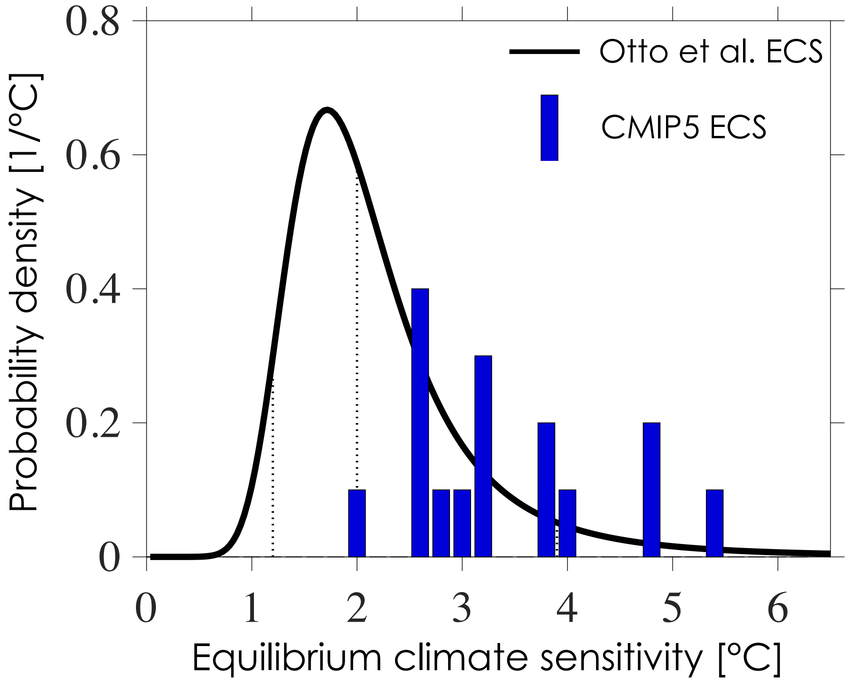
- Emerging consensus: model-observational comparisons must be made in a *like-with-like* way, accounting for possibility that:

  1) Feedbacks (λ) vary over time as the spatial pattern of warming evolves (Armour 2017; Proistosescu & Huybers 2017)

  2) Feedbacks affected by the "efficacy" of non-CO_2 forcings (Shindell 2014; Kummer & Dessler 2014; Marvel et al. 2015)

  3) Feedbacks depend on natural variability in the pattern of warming

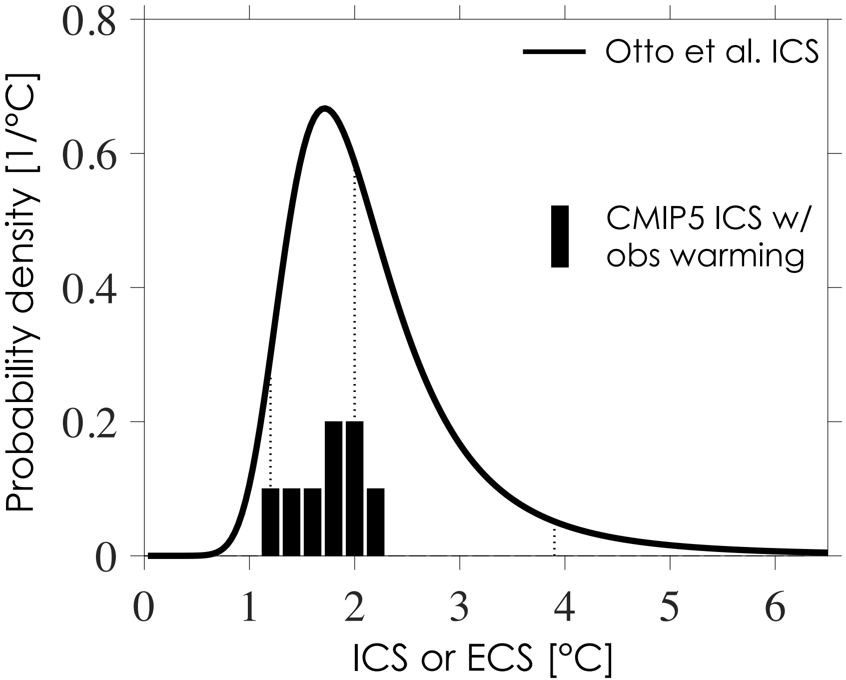
  4) Different definitions of global-mean temperature used in models vs observations (Cowtan et al. 2015; Richardson et al. 2016)



(Armour 2017; see also Proistosescu & Huybers 2017)

4) Sensitivity estimates depend on global temperature definition

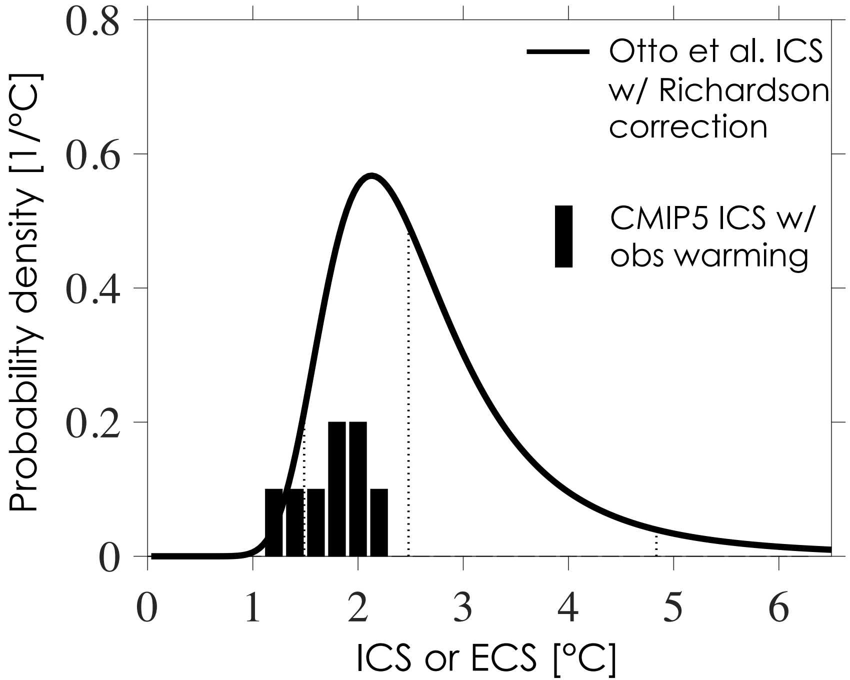
- Global temperature record is a blend of SST over ocean, near-surface air temperature over land; lacks full global coverage
- Global temperature in models is calculated as a full global average of near-surface air temperature



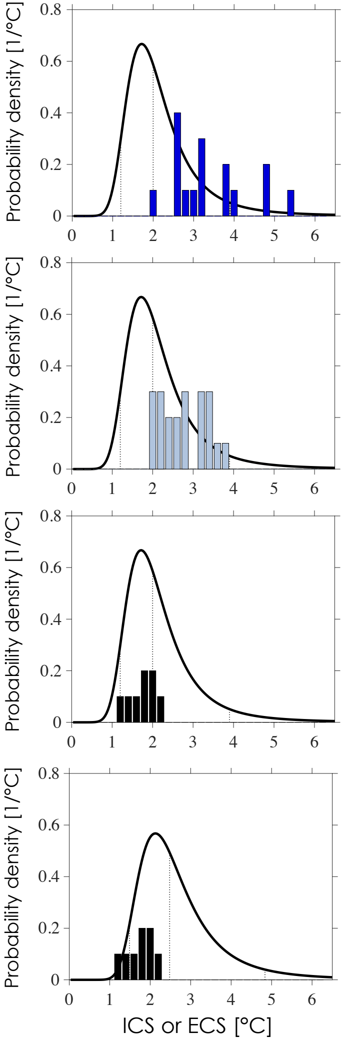
Prescribed observed SST simulations with CAM4, CAM5, HadGEM2, HadAM3, ECHAM6, AM2.1, AM3, AM4 (Yue Dong, Malte Stuecker, Cristi Proistosescu, Tim Andrews, Jonathan Gregory, Thorsten Mauritsen, Levi Silvers & David Paynter)

4) Sensitivity estimates depend on global temperature definition

- Global temperature record is a blend of SST over ocean, near-surface air temperature over land; lacks full global coverage
- Global temperature in models is calculated as a full global average of near-surface air temperature
- Blending/masking models consistently with observations suggests an increase to Otto et al. ICS estimate (Richardson et al. 2016)



Prescribed observed SST simulations with CAM4, CAM5, HadGEM2, HadAM3, ECHAM6, AM2.1, AM3, AM4 (Yue Dong, Malte Stuecker, Cristi Proistosescu, Tim Andrews, Jonathan Gregory, Thorsten Mauritsen, Levi Silvers & David Paynter)



Parting thoughts

- Apparent offset between global energy budget constraints and models stems from sloppy comparison between observation-based estimates of ICS and modeled estimates of ECS
- Accounting for feedback dependence on evolving pattern of CO_2-forced warming (slow warming of E. Pacific and Southern Ocean) gives model values of ICS that are in agreement with observation-based values (though still high)
- Accounting for the observed pattern of warming being pretty odd gives model values of ICS that are in good agreement
- Accounting for consistent global temperature definitions brings model ICS values to low end of observation-based ICS values